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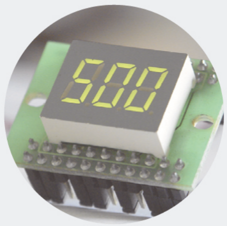

EFFICIENT USE OF DEMAND RESPONSE PROGRAMS: A CONSUMER-CENTRIC APPROACH

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RESUMO

O incremento do consumo de energia elétrica nas últimas décadas exige uma intervenção que pode e deve ser feita nos diversos aspetos dos sistemas elétricos. Várias propostas têm sido feitas para otimizar o uso da energia. No entanto, a necessidade de propor uma abordagem confiável para otimizar o consumo de energia dos edifícios é óbvia.

Esta tese propõe um sistema de gestão de energia para implementar programas de resposta da procura em diferentes tipos de edifícios. Foi desenvolvido um algoritmo de otimização para minimizar o consumo de energia dos edifícios. Neste contexto, vários tipos de cargas, nomeadamente luminárias e aparelhos de ar condicionado, são consideradas passiveis de redução. As máquinas de lavar, secar e ferro de engomar são consideradas cargas deslocáveis. Na abordagem de deslocamento de carga foi incluído o ciclo de operação de cargas deslocáveis. O algoritmo seleciona o melhor ponto de partida com base nos pesos de cada aparelho e na disponibilidade de energia em cada período. A função objetivo considera várias restrições para evitar a redução excessiva de energia. A contribuição científica desta tese está relacionada à integração das preferências do utilizador/consumidor e de indicadores de desempenho no algoritmo de otimização, considerando as cargas passiveis de redução e deslocáveis, bem como os recursos de geração nos edifícios.

Para validar o funcionamento do sistema, foram implementados 16 estudos de caso no âmbito de 16 artigos científicos desenvolvidos durante esta tese. Esses estudos de caso são classificados em três categorias com base na construção: escritório, residencial e industrial. Os resultados dos estudos de caso incluem os cálculos de todos os indicadores de desempenho e comprovam as funcionalidades do algoritmo de otimização. Os resultados demonstram como tal sistema pode efetivamente minimizar o consumo de eletricidade de acordo com os programas de resposta da procura.

Palavras-chave

Gestão de energia, Resposta da procura, Deslocação de consumos, Indicadores de desempenho.

ABSTRACT

The increment of energy consumption in the last decades takes a high level of attention in all network sectors. Many efforts have been made, and many solutions have been proposed by the experts to optimize energy use and propose an efficient energy management system. However, the need to propose a reliable approach for optimizing the buildings' power consumption is obvious to overcome the energy consumption issues.

This thesis proposes an energy management system to implement demand response programs in different types of buildings. In the core of this system, an optimization algorithm has been embedded to minimize the buildings' power consumption. In this context, various types of loads in the buildings, namely lights and air conditioners, are considered reducible, and curtailable loads and washing machines, dryers, and iron are considered shiftable loads. In the load shifting approach, the operation cycle of shiftable loads is included. The algorithm selects the best starting point based on the appliance weights and power availability in each period. The objective function considers various constraints to prevent excessive power reduction, according to user's preferences. The scientific contribution of this thesis is related to the integration of user preferences and key performance indicators in the optimization algorithm, considering the reducible and shiftable loads as well as generation resources in the buildings.

To validate the system's functionality, 16 case studies have been implemented in the scope of 16 scientific articles developed during this thesis. These case studies are classified into three categories based on building: office, residential, and industrial. The results of the case studies indicate the calculations of all performance indicators and prove the functionalities of the optimization algorithm. Furthermore, the results demonstrate how such a system can effectively minimize electricity consumption according to the demand response programs and using these flexibilities in the electricity markets.

Keywords

Energy Management, Demand Response, Key Performance Indicator, Load Shifting.

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ACRONYMS

AC	–	Air Conditioner
ACPI	–	Air Conditioner Performance Indicator
CAP	–	Capacity Market
CO2	–	Carbon Dioxide
CPP	–	Critical Peak Pricing
CSP	–	Curtailment Service Provider
DALI	–	Digital Addressable Lighting Interface
DBB	–	Demand Bidding/Buyback
DEC	–	Daily Electricity Cost
DG	–	Distributed Generation
DLC	–	Direct Load Control
DPP	–	Daily Peak Power
DR	–	Demand Response
DRER	–	Distributed Renewable Energy Resources
Dt	–	Deterministic
DTC	–	Daily Total Consumption
DTR	–	Daily Total Reduction
DTS	–	Daily Total shifting
EDRP	–	Emergency Demand Response Program
FERC	–	Federal Energy Regulatory Commission
H	–	Heuristic
HVAC	–	Heating and Ventilating Air Conditioner

IBR	–	Inclining Block rate
ICS	–	Interruptible/Curtailable Service
KPI	–	Key Performance Indicator
LP	–	Linear Problem
LPI	–	Light Performance Indicator
MIBEL	–	Iberian electricity market
MRR	–	Maximum Reduction Rate
OMPR	–	Optimization Modeling Package in Rstudio
OPT	–	Optimization
PLC	–	Programmable Logic Controllers
PV	–	Photovoltaic
PVPI	–	Photovoltaic Performance Indicator
RER	–	Renewable Energy Resource
RTP	–	Real Time Pricing
SCADA	–	Supervisory Control and Data Acquisition
TOU	–	Time Of Use
VPP	–	Virtual Power Player

NOMENCLATURE

C	–	Coefficient of performance
Dryer	–	Binary variable related to the dryer
DW	–	Dish Washer
E_AC	–	Energy consumption of air conditioner
E_Consumption	–	Energy consumption of the building
E_D	–	Energy consumption of the dryer
E_I	–	Energy consumption of iron
E_L	–	Energy consumption of light
E_PV	–	Energy generation of photovoltaic
E_WM	–	Energy consumption of washing machine
ER_AC	–	Energy reduction of air conditioner
ER_D	–	Energy reduction of the dryer
ER_I	–	Energy reduction of iron
ER_L	–	Energy reduction of light
ER_WM	–	Energy reduction of washing machine
inertia	–	Inertia factor
Max_AC_h	–	Percentage of nominal power consumption that determines the maximum allowed power reduction of the air conditioner in each specific time
Max_L_h	–	Percentage of nominal power consumption that determines the maximum allowed power reduction of light in each specific time
Max_L_R	–	Percentage of nominal power consumption that shows the maximum allowed power reduction of lights in each h

MaxRed_AC	–	Maximum allowed power reduction from a certain air conditioner in two consecutive periods
MaxRed_L	–	Maximum allowed power reduction from a certain light in two consecutive periods
N_D	–	Number of operations of dryer
N_I	–	Number of operations of iron
N_WM	–	Number of operations of washing machine
OF	–	Objective Function
P_AC	–	Power reduction of air conditioner
P_AC_Nom	–	Nominal power consumption of the air conditioner
P_L	–	Power reduction of light
P_L_Nom	–	Nominal power consumption of light
P_Max	–	Maximum power consumption limit in each period
Power_D	–	Power consumption of dryer
Power_I	–	Power consumption of iron
Power_WM	–	Power consumption of washing machine
Prio I	–	Priority number of iron
Prio_AC	–	Priority number of air conditioner
Prio_D	–	Priority number of dryer
Prio_L	–	Priority number of lights
Prio_WM	–	Priority number of washing machine
PRR	–	Power Reduction Rate
RR	–	Required Reduction
T_in	–	Indoor temperature based on power consumption of AC
T_Out	–	Outdoor temperature
T_set	–	Adjusted temperature by user
TC	–	Thermal conductivity

WM – Washing Machine

WM – Binary variable related to the washing machine

1 INTRODUCTION

This section presents an introductory discussion about the motivation of this thesis in section 1.1. Then, the thesis's objectives are outlined in section 1.2, which are related to the aspects identified in section 1.1. The outline and organization of the thesis are exposed in subsection 1.3.

1.1 MOTIVATION

Nowadays, electrical power systems are overgrowing. The process of controlling them takes a high level of attention from generation to consumption, and this growth is expected to increase by 30% by 2035 [1]. However, energy consumption has always been a concern for the world at various times [2].

The increment of energy consumption in the last decades has had irreparable consequences. Environmental problems such as global warming, melting glaciers, season replacements in many countries are clear examples of the aftermath of fossil fuel usage [3], [4], [5]. Many efforts have been made, and experts in this field have proposed many solutions, but each proposed solution has foibles that still make the energy consumption topics challenging. Renewable Energy Resources (RER) are presented as clean energy and can be considered as an alternative for fossil fuels; however, their uncertainty and stochasticity require comprehensive and accurate planning [6], [7].

In this context, power distribution networks are being updated and move towards the smart grid's paradigms. Smart grids bring a high level of flexibility for resource management; it means that different players can control their electricity consumption and generation [8]. On the other hand, the daily increment of electricity usage forced the network operators to reduce the use of fossil fuels and move towards sustainable and renewable energy resources, especially Photovoltaic (PV) systems and wind turbines [9].

In this context, the Demand Response (DR) program is a feature in the power system's new paradigms, which connect low carbon technologies without the need for reinforcement [10]. DR programs are defined as altering the end-users' consumption patterns in response to the price variations or incentive paid by a grid-side entity due to any economic or technical reasons [11]. There are two main categories for DR programs: incentive-based and price-based [12].

According to the definition mentioned above, the DR program can be considered as a function of total generation and electricity price variation during a day. This makes the consumers schedule the consumption based on these programs. They can control the consumption of appliances in response to electricity price variations under the DR programs, encouraging the consumers to shift their loads [13], [14]. All kinds of buildings can be considered promising targets for implementing DR programs and energy optimization approaches since they are responsible for energy consumption [15]. Consumption of building in all types is 40% of the world's energy consumption, and between 40% to 70% is belonged to Heating, Ventilation, and Air conditioning (HVAC) systems. It means that they are suitable cases for implementing DR programs and energy management approaches [16], [17]. Any change in the consumption pattern of users may cause discomfort for them. It is essential to consider users' preference and their convenience in energy management approaches; otherwise, those optimization approaches are not reliable and reasonable in the real-world [18].

Several research works in the literature reviewed the application and implementation of DR programs in buildings. According to the survey shown on [19] and [20], the DR program's implementation in automatic buildings requires various technologies, such as smart meter, home energy controllers, energy management systems, wired and wireless communication systems. Furthermore, the review presented in [21] identifies the controlling approaches for various types of loads in residential buildings for DR, namely lighting system, HVAC, and single home appliances such as refrigerators. Moving towards all types of consumers on the demand-side, the automatic DR program is applicable in residential buildings and is more enforceable on commercial and industrial sectors. The results of a survey in [22], demonstrate a great potential of the automatic commercial buildings to integrate DR programs individually, and also through aggregation model.

The use of price-based DR programs in automatic buildings is reviewed in several research articles. The reason is that the price of energy in such programs can be considered a control signal to modify electricity consumption. For example, in [23], the authors present a review of price-based DR programs applied in residential buildings. In the same work, they identified the requirements and installation infrastructures in the residential building for the automatic implementation of DR programs. In a similar work, the authors in [24] propose a new concept in integrated DR program. In this concept, not only can the consumers react to the DR programs by reducing electricity consumption or opting for off-peak consumption, but they can also change the type of consumed energy.

Therefore, the need for proposing a reliable approach for optimizing the power consumption of the buildings is obvious to overcome the energy consumption issues. This gap in the literature motivates the author of this thesis to present the contrast of accuracy and complexity in the scope of DR programs and building energy management by employing simple methods to control the actual devices in the real field.

1.2 OBJECTIVES

DR programs can be considered a practical energy management approach since they can encourage consumers to conserve energy during peak hours and high demand periods. These programs provide financial benefits for consumers, and also, they can increase the reliability of the grid. Different levels of automation in buildings bring different levels of participation in DR programs. It means that buildings can participate in different types of DR programs based on their equipment and infrastructure. These programs change users' consumption patterns by reducing or shifting their consumption; however, these modifications decrease their energy costs and profit. At the same time, these programs can increase users' discomfort and discourage them from continuing the program. So, it is essential to consider the comfort of users in energy management approaches.

Many studies and research work in the context of optimization-based energy management and DR implementation in the buildings. However, in most models, the users' comfort has been addressed by mathematical formulations and numerical case studies. Therefore, it deserves to use real data models in real pilots instead of just numerical studies. Therefore, the main objectives of this thesis are:

- Implementing and integrating algorithms in an optimization-based Supervisory Control and Data Acquisition (SCADA) system installed in a real office building;
- Developing contextual awareness algorithm using real-time data monitored by the SCADA system;
- Defining key performance indicators to validate the performance of the algorithm in various aspects;
- Implementing several actual case studies to prove the adequacy of the proposed approach;

To achieve the mentioned objectives above, this thesis contributes to:

- Designing and developing a multiperiod optimization algorithm to minimize the power consumption of a building;
- Designing and developing approaches to integrate the most recent updated users´ preferences in the optimization algorithm operation;
- Employing the load shifting approaches and load scheduling as a mean of consumption shifting;
- Conceiving and developing applicable features in the optimization algorithm to react to the user´s changes during the running period;

- Conceiving and developing intelligent decision making on when and how frequently the optimization algorithm requires to operate and run;

1.3 ORGANIZATION OF THESIS

This thesis consists of seven main chapters. After this introductory chapter, chapter 2 discusses a review on the state-of-the-art with a specific focus on DR programs and renewable resources and their integration in the building energy management system.

After that, chapter 3 provides the approach developed in this thesis to demonstrate how such approaches control the actual devices considering user comfort level. Then, in chapter 4, a specific vision is given to the optimization algorithm designed and developed in this thesis's scope, providing all mathematical models and equations.

In chapter 5, a diversity of case studies is presented to validate and test the proposed optimization algorithms' performance considering 16 published cases based on the proposing approach. The 16 base cases have been categorized in office, residential, and industrial buildings with different characteristics as performance analysis inputs. The results of these case studies are presented in chapter 6 to show the proposed methods' main achievements. Finally, chapter 7 exposes the main outcomes and findings gained through this thesis and also provides several paths for future works to be explored.

2 BACKGROUND AND CONCEPTS

The increment trend of electricity consumption in recent years causes a peak in greenhouse gas emissions. Employing Distributed Generation (DG), including Renewable Energy Resource (RER), contributes to overcoming this issue [25]. However, these resources make the power system unstable as they have variations in generation over time. Therefore, DR programs are applicable in this context to mitigate grid instabilities [26]. The main idea of this section is to present a review on the current state-of-the-art in the scope of RERs (subsection 2.1), DR programs (subsection 2.2), energy management system (subsection 2.3), the impact of user comfort in DR implementation (subsection 2.4), and surveying the role of key performance indicator in DR programs (subsection 2.5). Therefore, at the end of the section, the current literature's limitations and requirements for implementing DR programs are identified.

2.1 RENEWABLE ENERGY RESOURCES

The harmful effects of fossil fuels on the environment have caused many consequences such as global warming, melting the glaciers, and CO2 emissions. According to [26], global warming is becoming a more challenging issue in the next years. It should be noted that 36% of total Carbon Dioxide (CO_2) emissions belong to European buildings. The use of DG, including Renewable Energy Resource (RER), is essential in the smart grids and microgrid's implementation [27]. Their penetration has been raised as they are known as nature-friendly and green fuels [28]. The increase of renewables and prosumers as electricity production is expected to rise in years to come up to around 50% by 2024 compared with 2019 and up to two-thirds of energy consumption by 2050 [29], [30]. However, unlike conventional generation approaches, RERs are not reliable [31]. They are intermittent, and their uncertainty requires accurate management [32]. To find a solution for overcoming the mentioned issues, numerous studies agreed that the integration of RER and energy management approaches could reduce fossil fuel consumption and its consequences [33]. Also, the energy management approaches and forecasting techniques can increase RERs energy production efficiency by controlling their uncertainty and stochasticity [34][35].

2.2 DEMAND RESPONSE PROGRAMS

DR program is referred to as modification of consumption pattern by end-users in response to DR managing entities' incentive payment, which is due to any economic or technical reasons. According to the Federal Energy Regulatory Commission (FERC), a DR program is defined as "changes in electric use by demand-side resources from their normal consumption patterns in response to changes in the price of electricity, or to incentive payments designed to induce lower electricity use at times of high wholesale market prices or when system reliability is jeopardized" [14], [36], [37].

The idea of DR is a fact in the current distribution networks. It is referred to change users' consumption patterns based on electricity price variations or due to the technical or economic reasons in the wholesale markets. The main objective of DR is to manipulate the number of loads by the customer to meet the generating power and maintain the network in its stable state [38]. This process got important attention from the regulators. Therefore "they made efforts to make DR a resource compared to normal resources of generation. It is the order NO. 719 from FERC in the united states which said ''Accept bids from DR resources in their markets for certain ancillary services on a basis comparable to other resources'', also in the European Union, there are regulators had set important changes in this section to be applied. DR is to be understood as voluntary changes by end-customers of their usual electricity use patterns – in response to market signals (such as time-variable electricity prices or incentive payments) or following the acceptance of customers' bids (on their own or through aggregation) to sell in organized energy electricity markets their will to change their demand for electricity at a given point in time. Accordingly, DR should be neither involuntary nor unremunerated." [39], [40], [41].

DR programs can be categorized into two main groups, Price-based methods and Incentive-based methods. The incentive-based DR is related to a program that the customers are paid with the fixed or time-varying incentive provided by the grid operator [14]. Different DR programs can be categorized as below:

- Price-based methods refer to the variation of the consumer's energy consumptions to respond to the price variations [42]. Under this title, there are four programs can be included [14]:

    a) Time-Of-Use (TOU): In this method, the electricity price rates for consumers depend on the period of consumption. A day is typically divided into three categories, known as peak, mid-peak, off-peak, and the maximum rates will be on the peak periods. That lead to charge the consumers with different rates. In this way, they are encouraged to reduce their consumption at peak hours and shift their loads to off-peak hours [30].

    b) Real-Time Pricing (RTP): In this method of pricing, the electricity rates typically change by the hour, and that indicates the variations in the price of the wholesale electricity market. Typically, the consumers will be informed on a day-ahead or hour-ahead basis [44].

    c) Critical-Peak Pricing (CPP) rates: This method here is similar to TOU, but this is applied only when the reliability of the power system is endangered, and then the normal peak price is replaced by a very higher one. This program is only applied for very short periods per year and improves power system reliability [45].

    d) Inclining Block Rate (IBR): In this method, there are two levels of pricing, according to the amount of energy consumption of the consumers. When consumers reach a determined threshold of consumption, electricity rates will be higher [46].

- Incentive-based methods: it refers to the programs that give the consumers incentives for changing their consumption models. Some of these programs penalize consumers that fail during the events. Under this title, there are six programs can be included [14]:

  a) Direct Load Control (DLC): in this program, the operators install controlling devices in the customer's place, and they remotely shut down the customer’s electrical equipment. This program is mainly offered to small consumers, such as residential or small commercial customers [47].

  b) Interruptible/Curtailable Service (ICS): This program is based on reduction options integrated into market rates that provide a discount or bill credit by agreeing to reduce load during system contingencies and includes penalties for contractual response failures [48].

  c) In Demand Bidding/Buyback (DBB) programs: in these programs, the customers offer curtailment capacity bids at a certain bid price. This program typically large-scale consumers [49].

  d) Emergency Demand Response (EDRP): it is a combination of DLC and ICS and is applied in periods when the contingency reserve becomes insufficient [50].

  e) In Capacity Market (CAP): the customers offer load curtailment as system capacity to replace traditional generation or delivery resources [51].

In this concept, the end-users tend to participate in such programs to reduce their electricity bills by shifting their high consumption appliances to the off-peak hours or reducing their high consumption loads in peak hours [52]. Besides the DR programs, Distributed Renewable Energy Resources (DRERs) application in the demand side plays a key role in the smart grid. This means the consumers would supply their local demand through their own generation resources and sell energy to the network when they have a generation surplus [30]. Currently, most of the implemented DR programs are procured for large-scale resources. However, small-scale resources do not apply to these programs. It means typical small consumers, such as residential or commercial buildings, cannot participate in the DR programs individually. In order to overcome this issue, several concepts have been proposed. Virtual Power Player (VPP), and Curtailment Service Provider (CSP) are two concepts that can overcome the mentioned barrier. The DR aggregation is an impressive solution for participating of large volumes of consumers to wholesale electricity markets [53]. These concepts can be defined as an aggregation network that aggregates small and medium-scale consumers and prosumers and participate in the market as one. For the DR programs' real implementation, especially in the small and medium customers, the end-users should be equipped enough to receive the information regarding the DR events from DR managing entities and execute them [13].

According to the dataset provided by FERC [39], which presents the information about 2314 implemented DR programs, the commercial sector is more inclined to participate in DR programs than the other sectors. The percentage of participants in each customer type can be seen as below:

- 28% Residential
- 33% Industrial
- 39% Commercial

It should be noted that HVAC and lighting systems are the most common devices for DR implementation in commercial buildings.

As they are explained in previous parts, there are different types of DR programs with different characteristics. Figure 1 shows the percentage of participants in each program without considering the customer sector.

As can be seen in Figure 1, TOU has the highest percentage among the other programs. Second place and third place belong to DLC and ICS programs. To analyze the characteristics of DR programs and customers, it is important to survey different sectors' tendencies to the different types of DR programs. Figure 2 presents a categorization of all programs based on customer’s type and DR programs. As shown in Figure 2, residential customers are mostly motivated to participate in the DLC program. Household appliances can be considered as flexible and deferrable loads to be directly controlled.

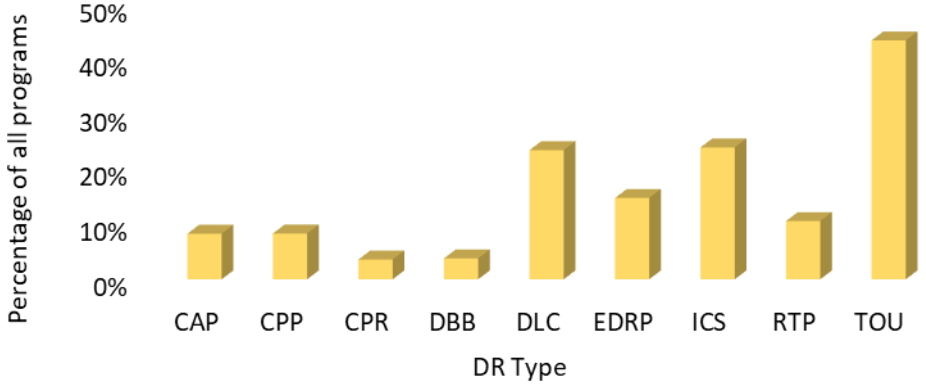

Figure 1. Percentage of participants in each DR program type, Adapted from [54]

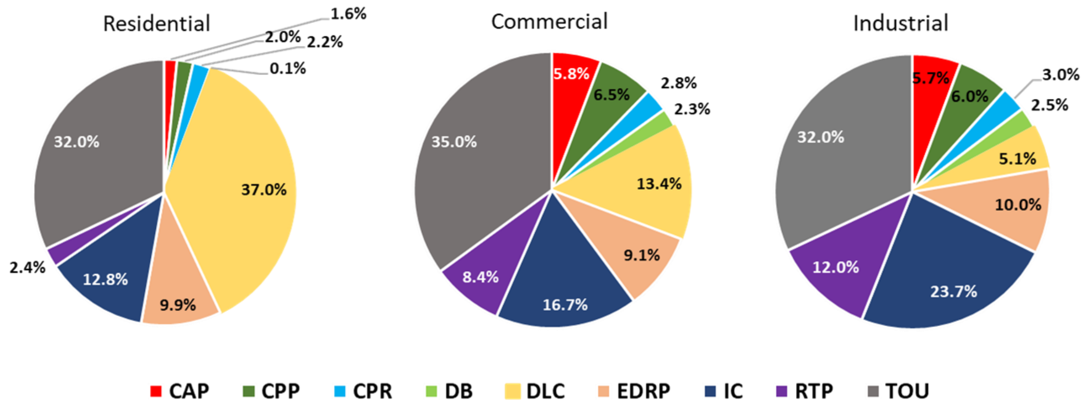

Figure 2. Customer's classes by DR program type, Adapted from [54]**.**

Comparison of DLC share in three classes shows that commercial and industrial sectors are not as flexible as residential customer's indirect control. TOU is another DR program method that is shown with an almost equal share in three types of customers. EDRP percentage in three classes are in the same range. It shows that customer class is not correlated to this type of DR programs since most customers have the option, but not the obligation, to sell their forgone energy to the grid during an emergency event.

2.3 Energy Management System

All types of buildings, including domestic, industrial, commercial, and office buildings, are responsible for 40% of world energy consumption. Office buildings can be considered flexible options for implementing DR programs since. Usually, they have significant energy consumption, and in some cases, can be more equipped with automation infrastructure than residential houses [18]. More attention is paid to Air Conditioners (AC) in office buildings, while 29% of total energy consumption in office buildings belongs to the lighting system. The lights of an office building can be considered as flexible loads for reduction and curtailment if they are fully controllable and reducible by existing [55].

However, the statistic of energy consumption shows that residential buildings consume quite a large percent of the global produced energy worldwide. Energy consumption for residential buildings represents the second-largest increase in energy consumption. For instance, in China, in 2015, 19.93% of the country's total energy consumption is consumed by residential buildings. Also, Globally, public and residential buildings account for 20.1% of the total delivered energy consumed. Figure 3 shows an overall view of an optimization-based building energy management system.

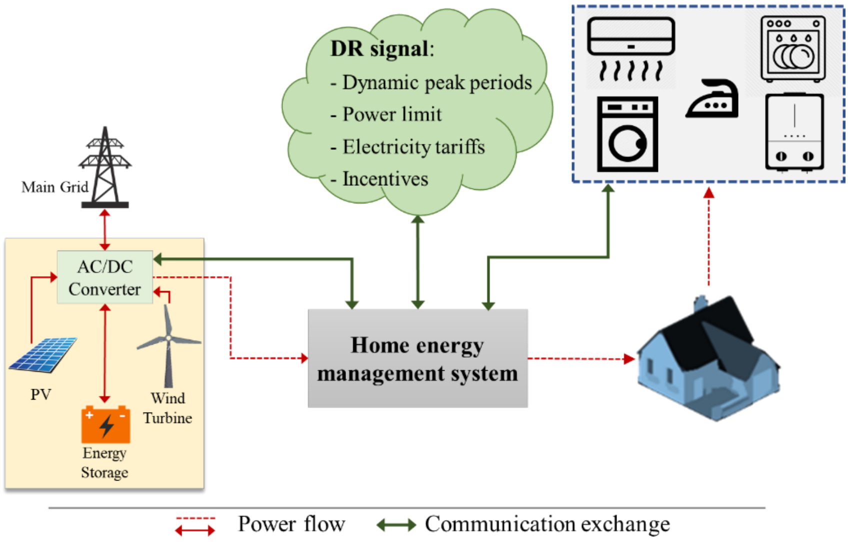

Figure 3. Overall view of a building energy management system, adapted from [30]

The industrial sector is considered an appropriate case for implementing DR programs because of the large size of individual industrial buildings and their flexibility in manufacturing processes. It means that electricity consumption in industrial buildings can be shifted from day to night if needed. On the other hand, due to the high consumption rate in peak load hours, the need for load shifting methods is more obvious [56]. However, the implementation of load shifting in residential and office buildings is not as easy as in the industrial sector because the user comfort and preferences are more highlighted.

Load shifting in industrial buildings is more useful since it does not affect the total energy demand. It affects the load profile shape by moving part of energy consumption from one period to another [57]. Load shifting approaches can reduce the peak demand and reduce the electricity costs of end-users. In this methods, electricity costs are considered a set point to shift the load from on-peak moments to off-peak hours [58]. Therefore, it is essential to identify the industrial loads' capabilities and characteristics to be involved in the load shifting approaches [59]. Depending on the use cases, load shifting can be considered an incentive-based DR program or price-based DR program. Generally, load shifting and its functionalities are in the scope of price-based control [60]. It means that shifting can be done to respond to electricity price variation, or it can be combined with RERs to move the consumer's load to high RER's generation periods. In this context, the peak loads cannot be simply shifted to off-peak hours as it can create a new peak in a new period. This invalidates the load shifting strategy and may not have financial profits for both network players and end-users [61]. Also, load shifting cannot be implemented intractably. Many constraints should be considered to obtain consumer preferences and grid requests. Also, loads' operation duration should be considered accurately to finish their cycles [57], [62].

In order to take advantage of DR programs and energy management approaches, the buildings should be equipped with automation infrastructures such as the SCADA system [63]. SCADA systems play a key role in DR implementation [64]. It offers various advantages to have automatic load control in different types of buildings [65]. For instance, the SCADA system can dominate the lighting system's illumination, which they are fully controllable via the Digital Addressable Lighting Interface (DALI) [66].

2.4 USER COMFORT

Recently, one of the main challenges of energy consumption optimizers is maintaining the balance between the program's goals and the convenience of users. According to the buildings' significant energy consumption, it should be noted that HVAC and illumination systems in buildings are the main consumers of energy. Furthermore, people spend a large part of their lives inside them, and the sensation of comfort determines their productivity; it also affects their health. For this reason, ensuring user comfort, which is strongly associated with HVAC and illumination systems control, has become a key issue in the energy management field [15], [67]. The three basic factors that determine the user's convenience in a building environment are thermal comfort, visual comfort, and air quality. Ideally, thermal comfort should be high, while the energy spent should be kept low. However, this does not hold for most of the time. It is well-known that higher comfort levels may require the consumption of more energy.

There is, of course, an unavoidable trade-off between energy consumption and occupant comfort. A poorly tuned system originates energy waste by consuming more energy than necessary and simultaneously keeping users uncomfortable. However, a typical scenario is consuming too much energy, while users would be willing to reduce their high comfort levels to an extent due to eco-friendly concerns. Also, in office buildings, visual comfort is very important as it directly affects users' efficiency, and the illumination level is used to indicate the visual comfort in a building environment [15], [68]. The user's satisfaction and user's preferences are very important in addition to three comfort factors (visual, thermal, and air quality). It means that optimization programs and energy management approaches should be flexible to respect the user’s preferences in the operating time of devices, the priority of devices, number of required operations, and sequence of operation. Table 1 has been prepared to present a summary based on a report in [69] that shows users' answers to the various questions related to their comfort.

Table 1. User satisfaction for participating in the residential DR program.

<table>
<tr><td rowspan="2">How often did the residence run out of hot water?</td><td>Once a week</td><td>Once a month</td><td>A couple of times per year</td><td>Never</td></tr>
<tr><td>7%</td><td>11%</td><td>38%</td><td>44%</td></tr>
<tr><td rowspan="2">How satisfying was the experience of participating in this pilot?</td><td>Neutral</td><td>Somewhat dissatisfied</td><td>Somewhat satisfied</td><td>Very satisfied</td></tr>
<tr><td>7%</td><td>1%</td><td>12%</td><td>80%</td></tr>
<tr><td rowspan="2">How likely are you to join a water heater control program?</td><td>Neutral</td><td>Somewhat unlikely</td><td>Somewhat likely</td><td>Very likely</td></tr>
<tr><td>4%</td><td>2%</td><td>22%</td><td>72%</td></tr>
<tr><td rowspan="2">What would be your primary motivation for joining a water heater control program?</td><td colspan="2">The amount of incentive I receive</td><td colspan="2">Other (environmental issues, help to build the new power plant, etc.)</td></tr>
<tr><td colspan="2">53%</td><td colspan="2">47%</td></tr>
</table>

It should be noted that proposing Table 1 is based on the DR program's real implementation with controlling the water heater of 164 residential customers.

2.5 KEY PERFORMANCE INDICATORS

Measuring and reporting performance is a key component in the goal of continuous improvement. Therefore, another important assessment of the sustainability of building energy management is key performance indicators (KPIs), which are categorized into several aspects such as energy consumption and resources saving, energy policy and audit, energy return ratio, Peak Energy Demand Reduction for building operations, thermal performance, use of daylight in the primary areas. KPIs can be used to identify performance of the components of system and the improvement potential. KPIs can be defined for individual equipment, or whole system depending on the specific situation and given the criticality in the identification of correlations between energy consumption and independent variables [70]. Different types of performances can be measured by KPIs, for example energy, raw material, control & operation, maintenance, etc.Before any actions towards reducing energy consumption can be implemented, a methodology is necessary to assess energy efficiency. There is a multitude of different energy-related key performance indicators. Besides energy, KPIs are used for other aspects, e.g., raw materials, operation time and quality, maintenance, planning, scheduling, and inventory and buffer utilization [71], [72].

3 User-Centric Management of Demand Response Programs

This section describes the optimization approach implemented to minimize the office building's power consumption considering user preferences and KPIs. The main purpose of the present approach is to optimize the power consumption of the buildings and validate the approach's performance based on different aspects. In subsection 3.1, the building energy management system presents the overall process of optimization approach. After that, subsection 3.2 shows the automation infrastructure and implemented the SCADA system for building management. Subsections 3.3, 3.4, and 3.5 present lighting management, AC management, and shift-able loads, respectively. The consideration of user comfort has been explained in 3.6. Subsection 3.7 described the focused aspects of user comfort and defined KPIs. Conclusions of respective section described in 3.8.

Another purpose of the present approach is to minimize the building's electricity cost based on several aspects. This approach manages the building's energy consumption based on DR program signals such as power consumption limits, dynamic peak periods, and monetary incentives. It should be mentioned that user preferences are important in the energy management concept. Users should specify the importance of the device, priority of use, and the required number of operations for shift-able loads in specific periods. Modification of user consumption patterns by an external entity could reduce user satisfaction. Therefore, several constraints should be considered to maintain user comfort.

3.1 BUILDING MANAGEMENT SYSTEM

This subsection illustrates the implementation of the optimization approach in the building. The first purpose of the algorithm is to reduce the required power reduction in each period. It means that there is a constraint for the required reduction, limiting the power consumption of devices. The desired power reduction in each period may alter depending on several aspects such as electricity price variation, the uncertainty of power generation, Peak or Off-Peak hours, and the situation of energy storage if it exists. It is important to achieve the desired power reduction of the algorithm whenever the required power reduction has been reduced at a balanced level from all the devices. For this purpose, several constraints and parameters are defined to consider user convenience. Another aim of the algorithm is to implement load shifting based on user decisions, electricity price variations, and power consumption limits. Figure 4 shows the SCADA system's overall architecture in an office building to implement the power reduction and sequential load shifting.

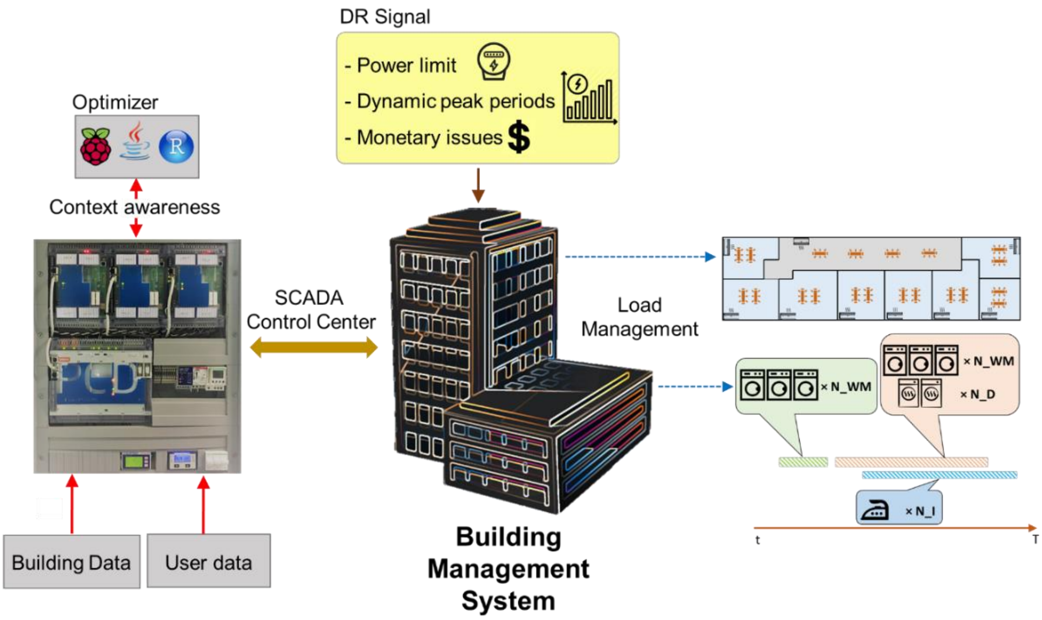

Figure 4. The overall architecture of the SCADA system in an office building.

It should be mentioned that the published articles during this thesis work bring several field implementations of a real building with the SCADA system. As shown in Figure 4, the building is equipped with a SCADA system that will be introduced by details in the next subsections. However, it should be mentioned that the main applications of this system are monitoring the consumption data, collecting the user data, and controlling the taking actions on the controllable loads. After the architecture of the optimization approach, Figure 5 shows the optimization approach's process to minimize the power consumption of the building and respective analysis.

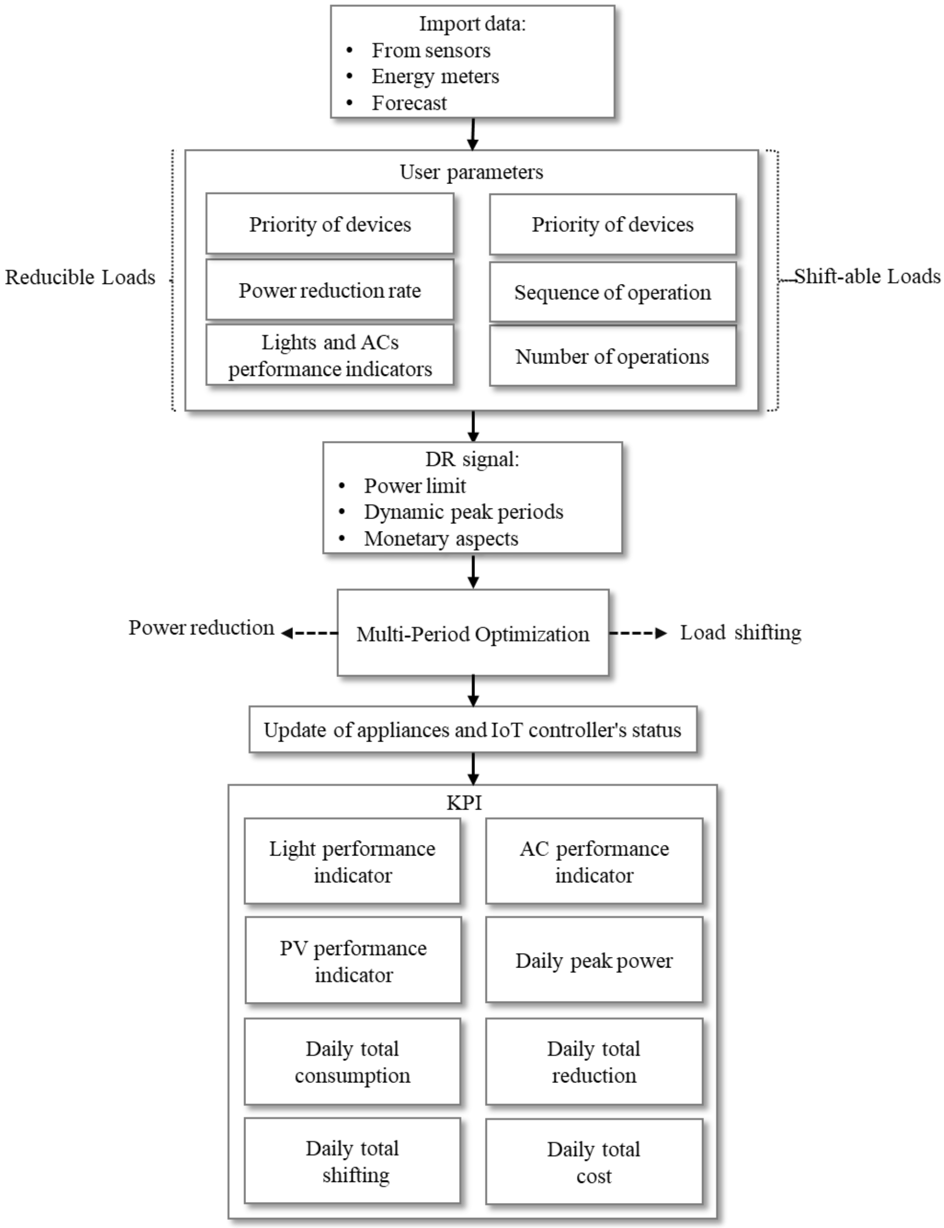

Figure 5. Process of proposed user-centric approach.

The present building consists of two parts, the first part as a normal office building and the second part as an industrial laundry. The controllable loads of office parts include lights and ACs, and controllable laundry room loads include WMs, dryers, and irons.

The lights and ACs are reducible, and interruptible loads are considered to achieve the method's power reduction purpose. Controllable laundry loads should complete their operation cycle and cannot be reduced; however, they are flexible with time and can be shifted from some periods to other periods based on several aspects. It should be mentioned that the proposed timeline presents the starting point of the optimization (t = 1) to the last period (t = T).

According to Figure 4, the DR signal notifies the system about the power consumption limit proposed by a smart meter. Also, peak periods and off-peak periods can be shown as power profiles to present the optimal periods for shifting. Monetary issues indicate the energy price variations and incentives if they exist.

Table 2 presents a summary of the characteristics of 16 implemented optimization approaches based on the proposed energy management system.

As shown in Table 2, all developed optimization problems have been defined as linear problems to minimize or shift the power consumption of buildings. It should be mentioned that all 16 problems have been implemented in Rstudio software (www.rstudio.com), using lpsolve and OMPR package. 75% of implemented methods focus on reducing power from reducible and power-adjustable loads, 37.5% of articles are implementing load schedule. It shows that three articles are considering power reduction and load scheduling at the same time. It can also be seen that DR programs such as DLC, RTP, and TOU programs have been implemented in some of those articles.

According to Table 2, the priority of devices is an important factor in the optimization problem's objective. However, other parameters, such as power consumption, required power reduction, energy cost, and user preference, are very important in devices' consumption patterns in different programs. Section 4 of this thesis will explain the impact of different algorithms' parameters in detail.

Table 2. Implemented optimization approach and objectives

Article	Approach						Objective							
	Optimization approach	power minimization	scheduling	load shifting	DR Programs	Price variation	Priority of devices	energy cost	power reduction	RER	user preference	consumption limit	KPI	CO2 concentration
[36]	LP-D	✓	-	-	DLC	-	✓	-	✓	✓	-	-	-	-
[66]	LP-D	✓	-	-	DLC	-	✓	-	✓	-	-	-	-	-
[13]	LP-D	✓	-	-	RTP	RTP	✓	✓	✓	✓	-	-	-	-
[33]	LP-D	✓	-	-	RTP	RTP	✓	✓	✓	✓	-	-	-	-
[73]	LP-D LP-H	✓	-	-	NA	-	✓	-	✓	-	-	-	-	-
[74]	LP-H	✓	-	-	NA	-	-	-	✓	-	-	-	-	✓
[55]	LP-D	✓	-	-	DLC	-	✓	-	✓	-	✓	-	-	-
[18]	LP-D	✓	-	-	DLC	-	✓	-	✓	-	✓	-	-	-
[15]	LP-D	✓	-	-	DLC	-	✓	-	✓	-	✓	-	-	-
[72]	LP-D	✓	✓	✓	DLC	-	✓	-	✓	-	✓	-	✓	-
[68]	LP-D	✓	✓	✓	DLC	-	✓	-	✓	-	✓	-	-	-
[30]	LP-D	✓	✓	-	DLC CAP	TT	-	✓	✓	✓	-	-	-	-
[54]	LP-D	✓	-	-	DLC	-	✓	-	✓	-	-	-	-	-
[75]	LP-D	-	✓	✓	TOU	DT	✓	✓	-	-	-	✓	-	-
[76]	LP-D	-	✓	✓	TOU RTP	DT	-	✓	-	-	✓	✓	-	-
[57]	LP-D	-	✓	✓	TOU RTP	DT RTP	✓	✓	-	-	✓	✓	-	-

3.2 SCADA SYSTEM

To present the details of the methodology, this subsection illustrates the SCADA system to control the building's consumption. The automation infrastructures have been implemented in a part of the GECAD research center building, which contains eight offices, one server room, and a corridor. Moreover, there is a 7.5 kW PV installation on the building, which supplies a part of total consumption. To manage the building's consumption, three distributed based Programmable Logic Controllers (PLCs) dedicated for a zone including three offices. Therefore, there are three zones some-how each PLC associated with one zone.

Moreover, there is a main PLC that is responsible for supervising the other distributed based PLCs. The SCADA system's main controlling panel, including all PLCs, can be seen in Figure 4. This SCADA system's loads associated to be controlled and managed include illumination systems, ACs, and electrical sockets controlled by several communication protocols.

Also, the real-time consumption of the building is measured through several energy meters. In this model, there are five main agents that each of which is run by a Raspberry Pi (www.raspberrypi.org). Three PLC, PLC1, PLC2, and PLC3 are devoted to each zone, where these agents are equipped with a PLC for performing controlling decisions locally.

3.3 LIGHTING CONTROL

In this approach, the consumption optimization of lights is based on their priority to observe user preference. It means that the power consumption of lights will be reduces based on their importance. Priority numbers are decimal numbers between 0 and 1, which shows their importance for the user. In this way, the priority numbers close to 0 are the low priorities, and the numbers near to 1 are the most important lamps for users, based on its location and user preferences.

These priority numbers observe the user comfort to some extent, but more restrictions are required to prevent any exorbitance reduction. For this purpose, several constraints are provided to limit power reduction more than enough. Since the present algorithm is a multi-period optimization approach, there is full control of each light in all periods. Therefore, the algorithm can prevent the reduction of more than enough from only some particular lights in continuous periods. It means the situation of each light changes during all periods by comfort constraints and priority numbers. Also, there is a bound for consumption reduction of each light because any room should not completely lose its lighting. After optimization, the intensity of each light is a value between minimum reduction (=0) and maximum reduction (=defined by user) based on their priority and importance.

The lighting system is controlled through the DALI ballast, which is connected to a PLC that manages the intensity of the illumination and the discrete control (ON or OFF). Moreover, several energy meters mounted on the different parts of the building that measure the lighting system's consumption with 1 second time interval. In the meantime, the PLC requests the real-time power consumption data from each energy meter through an industrial protocol called Modbus RTU-RS485. Finally, the PLC transmits all information to a central database with a 10 seconds time interval via the Modbus TCP/IP transmission protocol. The information includes the timestamp (including date and time), the lighting system's power consumption data, and the light intensity for every two fluorescent lamps.

3.4 AC CONTROL

According to several studies such as [18], ACs are responsible for a large part of the building's energy consumption and are suitable cases for reduction purposes. In this optimization approach, ACs are the main reducible loads to achieve the required reduction of methodology. Since there is more than one AC in office buildings, the priority numbers should indicate each device's importance. Similar to the lights, an importance weight is defined for each AC to rank the priority of each device for the user. The importance weights are shown by a number between 0 and 1, in which the biggest number is dedicated to the most important AC.

It should be noted that the priority numbers can be adjusted by the respective user of the device. ACs can be considered as reducible or curtailable loads. However, in this approach, ACs are reducible loads with specified bounds. It means that the power reduction of ACs is between minimum reduction (=0) and maximum reduction (≤ nominal power consumption). In order to maintain the thermal comfort of users, several constraints named comfort constraints are provided to bound the power reduction.

The present algorithm is a multi-period optimization algorithm able to survey entire states of devices in all periods. Therefore, the algorithm attempts to prevent successive power reduction from only certain devices.

Regarding the AC optimization, an Arduino® (www.arduino.cc) equipped with an Ethernet Shield and an Infrared Light-Emitting Diode (IR LED) have been programmed and installed near to each AC. This controlling scenario emulates the remote control of ACs; somehow the SCADA takes the decision for each AC and transmits the desired command to each AC controller (Arduino®) via Ethernet interface; Arduino controls the AC based on the SCADA decision (turn OFF/ON, and regulating the temperature) for DR participation.

3.5 LOAD SHIFTING

In the present load shifting technique, the devices' power consumption should be shifted from some periods to next or previous periods depending on the desired conditions, such as economic or technical reasons. In such appliances, the operation cycle is critical. It leads to several limitations in the operation scenarios, namely when a device starts to operate, where the cycle should be completed, and cannot be interrupted before finishing the cycle. Therefore, the selection of the starting point of load shifting in the optimization algorithm requires careful consideration. Accordingly, priority parameter figures have been dedicated to each period to determine each period's capability to receive the shifted load.

According to the definition of DR programs, they can influence the power consumption pattern of users based on energy price variations, technical problems, and incentives. DR programs can set power consumption limits in each period based on the mentioned issues. It means that they ask users to reduce their consumption based on allowed power or shift their consumption to no limit periods. In the present approach, if the power consumption of devices is more than the power limit, they should be shifted to other periods to observe the DR signal. Electricity price has a strong effect on the time of using electricity. It means that power consumptions are eager to locate in off-peak periods. However, they should observe the other conditions. Incentives can be determinant in the implementation of load shifting to minimize the energy bill as much as possible.

From the realistic perspective of users, some devices' operation cycles must be after finishing the other ones' operation cycle. In this case, some devices are free to have interference in their operation cycle, but for example, the starting time of dryers should be after the complete operation cycle of washing machines. This optimization approach considers devices' priority to operate and considers energy prices and incentive prices in different periods. Regarding DR program specifications, devices' power consumption should be shifted to the desired periods by considering the dryers' operation cycle.

In the context of shift-able loads, it should be mentioned that user preferences are important in the energy management concept. Users should specify the required number of operations for each device in specific periods.

3.6 CONTEXTUAL AWARENESS BASED ON USER COMFORT

This subsection indicates the process of consideration of user comfort based on focused issues. The present reducible loads, including lights and AC, are directly related to visual comfort and thermal comfort. Therefore, several constraints have been defined to limit each device's excessive overall power reduction and limit power reduction in consecutive periods.

As described, priority numbers are determinant parameters in the present algorithm which they have a key role in each device's destination during all periods. The priority criteria adjustments need a comprehensive survey on user preferences based on the history of behavior, or sometimes it can be adjusted by the user itself. Each device's location in the building and time information is also the other aspect of priority number definition. In addition to priority numbers, there is another important parameter in the algorithm, which plays a determinative role in reducing power reduction from each device. The main purpose of the Power Reduction Rate (PRR) definition is balancing the power reduction among all ACs and lights. The algorithm's main purpose is to minimize the power consumption of the device at a certain value by observing all existing constraints. PRR is a general parameter to limit the total power reduction in all periods; however, other parameters can be mentioned as special PRR. It means that they can limit the power reduction for special devices and special periods.

Another parameter called Maximum Reduction Rate (MRR) is to avoid reducing power consumption from devices in consecutive periods. After specifying the parameters, the relative constraints should define, and the variables should bound. The desired purpose of the algorithm is minimizing a certain amount of power consumption from the devices.

3.7 KEY PERFORMANCE INDICATOR COMPUTATION

To validate the performance of the present approach, different KPIs have been defined based on different aspects. As mentioned, the results of optimization come with the modifications in the power consumption of devices. It means that in all periods, each load's power consumption will be reduced, will be shifted, or rarely with no modifications. In the case of power reduction, Light Performance Indicator (LPI) and Air Conditioner Performance Indicator (ACPI) have been defined to propose each different device's performance. LPI and

ACPI represent the total power reduction of devices in all periods to initial power consumption.

RERs are important in the optimization methods for both consumers and producers to reduce the electricity cost and use of fossil fuels. In addition to LPI and ACPI, there is a defined KPI to propose the performance of RERs in DR program implementations and energy management methods. These KPI are based on total RER generation and the other productive parameters such as total consumption. In the present thesis, PV generation has been considered as the main RER unit. However, this concept applies to other units with similar nature, such as wind turbines.

The ratio of total energy generation of PV to total energy consumption is considered as PVPI to propose the performance of the PV unit based on total demand. It is obvious that higher PVPI indicates the PV unit; however, energy storage can be employed to store the surplus of generation.

The next KPIs have been considered to propose the performance of the system in determinant aspects such as Daily Peak Power (DPP), Daily Total Consumption (DTC), Daily Total Reduction (DTR), Daily Total Shifting (DTS), and Electricity Cost (EC). These indicators validate the system's overall conditions, and they are effective in the final outcomes.

3.8 CONCLUSIONS

As can be seen in previous subsections, the steps of proposed approach have been described in detail. This method aimed to minimize the power consumption of the building by considering user comfort. In the first part, the overall view of the energy management system has been illustrated to present the optimization method's steps. It was proposed that input data such as consumption data and user data are important parts of the methodology. Subsection 3.2 proposed that input data are collected by the SCADA system, which contains several energy meters and PLCs.

To minimize the power consumption of the building, lights and ACs have been obligated to reduce their power reduction to achieve the power reduction goals. It was explained that these power reductions should be made based on the priority of devices. Also, shiftable loads have been considered to implement the load shifting based on the priority of devices, number of operations, and the sequence of operations.

The comfort of users may be affected by modifications in the consumption pattern of users. Therefore, several constraints have been defined for respect to the user's preference. In this approach, the user can specify their participants in minimization based on time and place. Also, comfort constraints ensure that all devices participate fairly in optimization.

4 ENERGY RESOURCE MANAGEMENT OPTIMIZATION

This section presents the linear optimization problem to minimize the building's power consumption by using the available loads and available generations, consideration of user comfort, and defining related KPIs. In this context, the algorithm should decide optimally what should be changed in the available resources. The present optimization approach is developed in Rstudio® software using the OMPR package, one of the available packages in Rstudio® for solving linear and mixed-integer linear problems.

The following parts include subsection 4.1 to present the objective function of the optimization approach. Subsection 4.2 presents the constraints related to the power reduction and load balance. Subsection 4.3 shows and explains the constraints related to the load shifting. The comfort constraints related to power reduction have been presented in subsection 4.4. In subsection 4.5 shows the mathematical formulation related to the different KPI calculations. Subsection 4.6 presents the conclusions of the section.

4.1 OBJECTIVE FUNCTION

This subsection presents the following equations to illustrate the present optimization approach's objective function (OF). The optimization solver changes the variables in this equation to find the combination of the values that minimizes power consumption, electricity costs, respecting the priority of each variable. The main OF for the present methodology is presented in (1).

$$\begin{aligned} Minimize\ OF = \sum_{t=1}^{T} \Bigg[& \sum_{l=1}^{L} Prio\_L_{(l,t)} \times P\_L_{(l,t)} \\ & + \sum_{a=1}^{A} Prio\_AC_{(a,t)} \times P\_AC_{(a,t)} + \frac{T\_in_{(a,t)} - T\_set_{(a,t)}}{T\_in_{(a,t)}} \\ & + \sum_{o=1}^{O} \sum_{m=1}^{M} (Prio\ \_WM_{(o,m)} \times Price_t \times Power\_WM_{(o,m,t)} \times WM_{(o,m)}) \\ & + \sum_{od=1}^{OD} \sum_{d=1}^{D} (Prio\_D_{(od,d)} \times Price_t \times Power\_D_{(od,d,t)} \times Dryer_{(od,d)}) \\ & + \sum_{oi=1}^{OI} \sum_{i=1}^{I} (Prio\_I_{(oi,i)} \times Price_t \times Power\_I_{(oi,i,t)} \times Iron_{(oi,i)}) \Bigg] \end{aligned} \tag{1}$$

P_L and *P_AC* are integer variables related to the power level of lights and ACs, respectively. But the variables related to the shiftable loads such as *WM*, *Dryer*, and *Iron* are binary variables to represent the operation state of devices. It is clear that one is related to the ON situation and 0 s related to the OFF situation. *L* and *A* indicates the maximum number of lights and AC, respectively. *M*, *D*, and *I* mean the maximum number of WM, dryer, and iron, respectively. *T* shows the maximum number of periods.

Prio_L and *Prio_AC* present the priority of lights and ACs, respectively, to reduce their power consumption. However, *Prio_WM* represent the priority of WM to shift, *Prio_D* means the priority of dryer for participating in load shifting, and *Prio_I* shows the priority of iron for shifting its consumption to other periods. Priority numbers are considered decimal numbers between 0 and 1 to determine each device's priority to participate in the DR event based on user preference. The larger numbers correspond to the important device for the users and vice versa. O means the maximum number of possible operating modes for WM. O*D* means the maximum number of possible operating modes for the dryer. *OI* means the maximum number of possible operating modes for iron.

In (1), *Price* means the energy price in different periods t. *Price* can be considered based on different tariffs such as simple tariffs, double tariffs, triple tariffs, and dynamic tariffs. *Power_WM*, *Power_D*, and *Power_, I* indicate WMs, dryers, and iron's power consumption, respectively, to give the power weight to the binary variables. OF has been defined to minimize the building's power consumption based on the user’s choice and preference. However, there is another approach to consider users' comfort by focusing on temperature variation on the power consumption of ACs. Regarding temperature, *T_in* indicates the indoor temperature of each office in each period that the algorithm should select the respective *T_in* based on the following constraints. *T_set* shows the set temperature by the user that can be different in each period of a day.

Obviously, (1) indicates the main objective function of method; however, available loads and data determine the application of each part of OF.

4.2 LOAD BALANCE CONSTRAINTS

Equation (2) represents the amount of required power reduction and load balance in each distinct period. In this context, ACs and lights are obligated to achieve the amount of required power reduction. According to (2), the reduced power from lights and ACs can be considered total power reduction in each period.

$$\sum_{l=1}^{L} P\_L_{(l,t)} + \sum_{a=1}^{A} P\_AC_{(a,t)} + \sum_{u=1}^{U} PV_{(u,t)} = RR\ ;\ \forall\ 1 \leq t\ \leq T \tag{2}$$

Also, there is a limit for power consumption of shiftable loads in each period. It should be mentioned that *P_max* is related to the total power consumption of shiftable devices. Equation (3) presents the power consumption limit in each period.

$$\begin{aligned}\sum_{o=1}^{O}\sum_{m=1}^{M}(Power\_WM_{(o,m,t)} \times WM_{(o,m)}) \\ + \sum_{od=1}^{OD}\sum_{d=1}^{D}(Power\_D_{(od,d,t)} \times Dryer_{(od,d)}) \\ + \sum_{oi=1}^{OI}\sum_{i=1}^{I}(Power\_I_{(oi,i,t)} \times\ Iron_{(oi,i)}) \leq P\_Max_t; \forall\ 1 \leq t \leq T\end{aligned} \tag{3}$$

The amount of RR can be changed based on the electricity price, technical issues, and peak demands.

4.3 LOAD SHIFTING CONSTRAINTS

This subsection illustrates the defined constraints related to load shifting. As mentioned, users can specify the number of operations for each device based on their requirements. Also, it is possible to define the specific time for each operation. Equations (4) to (6) are the constraints for choosing the number of operations for WM, dryer, and iron, respectively. Each constraint can be broken into several series to specify the time for each operation.

$$\sum_{o=1}^{O} WM_{(o,m)} = N\_WM_m \; ; \; \forall\, m \in \{1, \dots, M\} \tag{4}$$

$$\sum_{od=1}^{OD} Dryer_{(od,d)} = N\_D_d \; ; \; \forall\, d \in \{1, \dots, D\} \tag{5}$$

$$\sum_{oi=1}^{OI} Iron_{(oi,i)} = N\_I_i \; ; \; \forall\, i \in \{1, \dots, I\} \tag{6}$$

N_WM shows the number of operations for WM. *N_D* is related to the number of operations for the dryer, and *N_I* indicates the number of iron operations.

Regarding the rational use of devices, (7) and (8) are defined to observe the operation sequence. Equation (7) allocates the operation cycle of dryers after WMs, and (8) is prepared to locate the starting point of iron after the complete operation cycle of dryers.

$$\sum_{o=1}^{O} o \times WM_{(m,o)} \leq \sum_{od\,=\,OCM+1}^{OD} od \times Dryer_{(d,od)} \; ; \forall\, m \in \{1, \dots, M\} ; \forall\, d \in \{1, \dots, D\} \tag{7}$$

$$\sum_{od=1}^{OD} od \times Dryer_{(d,od)} \leq \sum_{oi=\,OCD+1}^{OI} oi \times Iron_{(i,oi)} \; ; \forall\, d \in \{1, \dots, D\} ; \forall\, i \in \{1, \dots, I\} \tag{8}$$

OCM shows the number of periods for the complete operation cycle of washing machines. OCD shows the number of periods for the complete operation cycle of dryers.

4.4 Comfort Constraints

This subsection presents the defined constraints for limiting the power consumption of lights and ACs based on user preference. Equations (9) and (10) limit the total power consumption of lights and AC in all periods by *PRR_L* and *PRR_AC*, respectively, to comfort level 1.

$$\sum_{t=1}^{T} P\_L_{(l,t)} \le \sum_{t=1}^{T} PRR\_L_{(l,t)} \times P\_L\_Nom_{(l,t)};\ \forall\, 1 \le l \le L \tag{9}$$

$$\sum_{t=1}^{T} P\_AC_{(a,t)} \le \sum_{t=1}^{T} PRR\_AC_{(a,t)} \times P\_AC\_Nom_{(a,t)};\ \forall\, 1 \le a \le A \tag{10}$$

PRR_L and *PRR_AC* are the maximum allowed power reduction for each device in different periods. When *PRR_L* and *PRR_AC* are equal to one, it means the device is available to turn off. To consider users' preference based on time, equations (11) and (12) present the limitation of power reduction for lights and ACs, respectively, based on specific hours of the day.

$$\sum_{t} P\_L_{(l,t)} \le \sum_{t}\sum_{h=1}^{H} \left(Max\_L\_h_{(l,h)} \times P\_L\_Nom_{(l,t)}\right);\ \forall\, 1 \le l \le L; \\ \forall\, t = 1-4;\ 5-8;\ 9-12;\ 13-16;\ 17-20;\ 21-24; 25-28; 29-32; 33-36; 37-40; 41-44; 45-48; 49-T; \tag{11}$$

$$\sum_{t} P\_AC_{(a,t)} \le \sum_{t}\sum_{h=1}^{H} \left(Max\_AC\_h_{(a,h)} \times P\_AC\_Nom_{(a,t)}\right);\ \forall\, 1 \le a \le A; \\ \forall\, t = 1-4;\ 5-8;\ 9-12;\ 13-16;\ 17-20;\ 21-24; 25-28; 29-32; 33-36; 37-40; 41-44; 45-48; 49-T; \tag{12}$$

It should be noted that equations (11) and (12) are open to being adjusted based on users' timetables and preferences. In the same equations, *Max_L_h* is the particular state of *PRR_L*, and *Max_AC_h* is the appearance of *PRR_AC*. It should be noted that one h is divided into four periods in Equations (11) and (12). As it is clear, the amount of natural light depends on the architecture of each room and the geographical location of the room. To take advantage of natural light in each room, equation (13) sets the maximum allowed power reduction of each light based on the room's architecture and geographical conditions with a defining *Max_L_R* parameter.

$$\sum_{l} P\_L_{(l,t)} \le \sum_{l} Max\_L\_R_{(r,t)} \times P\_L\_Nom_{(l,t)};\ \forall\, 1 \le r \le R;\ \forall\, 1 \le t \le T;\ \forall\, l = 1-2;\ 3-4;\ 5-6; \dots;\ 17-18;\ 19-20;\ 21-L \tag{13}$$

It should be noted that (11), (12), and (13) provide comfort level 2. Focusing on the user comfort, the power reduction in consecutive periods for a certain device can be annoying for the user because the user could feel a light reduction or thermal inconvenience for a prolonged period. Therefore, Equations (14) and (15) are assigned to prevent power reduction of certain lights and ACs, respectively, in consecutive periods for providing comfort level 3.

$$P\_L_{(l,t)} + P\_L_{(l,t-1)} \leq MaxRed\_L * P\_L\_Nom_{(l,t)} ; \forall\, 1 \leq l \leq L; \forall\, 2 \leq t \leq T \tag{14}$$

$$P\_AC_{(a,t)} + P\_AC_{(a,t-1)} \leq MaxRed\_AC * P\_AC\_Nom_{(a,t)}; \forall\, 1 \leq a \leq A; \forall\, 2 \leq t \leq T \tag{15}$$

As can be seen in Equation (14), the power reduction of each light in two consecutive periods is limited by *MaxRed_L*, and MaxRed_AC has restricted the power reduction in each *AC* for two consecutive periods by (15).

In addition to the previous constraints, the algorithm should find the corresponding power consumption at each period to preserve the set temperature by users to consider comfort level 4. Equation (16) shows the relation between indoor and outdoor temperatures in two successive periods [8].

$$T\_in_{(a,t)} = \left(inertia \times T\_in_{(a,t-1)}\right) + (1 - inertia) \times \left(T\_out_{(a,t-1)} - \left(\frac{C}{TC} \times \left(P\_AC\_act_{(a,t-1)} - P\_AC_{(a,t-1)}\right)\right)\right); \forall\, 1 \leq a \leq A; \forall\, 2 \leq t \leq T; \forall\, T_{in(a,1)} = K \tag{16}$$

In (16), *inertia* represents the inertia factor, *C* is related to the performance coefficient. *TC* shows the thermal conductivity. It should be noted that *P_AC_act* means the actual power of AC.

4.5 Key Performance Indicator Formulations

This subsection presents the formulations related to the defined KPIs. Each KPI represents a specific meaning of loads performance in the implementation of the algorithm. Equations (17) and (18) illustrate the *LPI* and *ACPI*, respectively.

$$LPI_l \geq \frac{\sum_{t=1}^{T} P\_L_{(l,t)}}{\sum_{t=1}^{T} P\_L\_Nom_{(l,t)}}; \forall\, 1 \leq l \leq L \tag{17}$$

$$ACPI_a \geq \frac{\sum_{t=1}^{T} P\_AC_{(a,t)}}{\sum_{t=1}^{T} P\_AC\_Nom_{(a,t)}};\ \forall\, 1 \leq a \leq A \tag{18}$$

As shown in (17) and (18), *LPI* and *ACPI* show the ratio of power reduction of devices in all periods to initial power consumption. It can be interpreted that comfort constraint reduces these parameters to maintain the user's convenience.

According to the 3.7, a KPI has been defined to propose the PV unit's performance by the division of total PV generation on total energy consumption. Equation (19) indicates the mathematical formulation related to *PVPI*.

$$PVPI = \frac{\sum_{t=1}^{T} E\_PV_t}{\sum_{t=1}^{T} E\_Consumption_t} \tag{19}$$

Equation (20) proposes the DPP to be applicable for reducing network congestions.

$$DPP = Max(Power_t, 1 \leq t \leq T) \tag{20}$$

Equations (21) to (24) indicate DTC, DTR, TSP, and EC, respectively.

$$\begin{aligned} DTC = \sum_{t=1}^{T} \Bigg(& \sum_{l=1}^{L} E\_L_{(l,t)} \\ & + \sum_{a=1}^{A} E\_AC_{(a,t)} + \sum_{m=1}^{M} E\_WM_{(m,t)} + \sum_{d=1}^{D} E\_D_{(d,t)} \\ & + \sum_{i=1}^{I} E\_I_{(i,t)} \Bigg) \end{aligned} \tag{21}$$

$$\begin{aligned} DTR = & \sum_{t=1}^{T} \sum_{l=1}^{L} ER\_L_{(l,t)} \\ & + \sum_{t=1}^{T} \sum_{a=1}^{A} ER\_AC_{(a,t)} + \sum_{t=1}^{T} \sum_{m=1}^{M} ER\_WM_{(m,t)} \\ & + \sum_{t=1}^{T} \sum_{d=1}^{D} ER\_D_{(d,t)} + \sum_{t=1}^{T} \sum_{i=1}^{I} ER\_I_{(i,t)} \end{aligned} \tag{22}$$

$$DTS = \sum_{t=1}^{T}\left(\sum_{o=1}^{O}\sum_{m=1}^{M}(E\_WM_{(o,m,t)} \times WM_{(o,m)}) + \sum_{od=1}^{OD}\sum_{d=1}^{D}(E\_D_{(od,d,t)} \times Dryer_{(od,d)}) + \sum_{oi=1}^{OI}\sum_{i=1}^{I}(E\_I_{(oi,i,t)} \times Iron_{(oi,i)}) + \sum_{a=1}^{A} E\_AC_a\right) \tag{23}$$

$$DEC = \sum_{t=1}^{T}\left[\left(\sum_{l=1}^{L} E\_L_{(l,t)} + \sum_{a=1}^{A} E\_AC_{(a,t)} + \sum_{m=1}^{M} E\_WM_{(m,t)} + \sum_{d=1}^{D} E\_D_{(d,t)} + \sum_{i=1}^{I} E\_I_{(i,t)}\right) \times Price_t\right] \tag{24}$$

4.6 CONCLUSIONS

As shown in previous subsections, the mathematical formulations of optimization approach have been presented based on all aspects. The first subsection presented the main objective function, after that required reduction, and the algorithm's consumption limits have been shown. The implementation of load shifting needs the definition of several constraints to specify the number of operations and sequence of operating. Therefore five equations have been defined to achieve these aspects.

User comfort constraints focused on the amount of power reduction of lights and ACs based on time, place, and total reduction. Also, the power reduction of devices in two consecutive periods has been limited by two comfort constraints. It can be mentioned that seven comfort constraints have been designed based on user choice and user preference. However, one constraint was proposed to adjust air conditioners' power consumption based on outdoor temperature, indoor temperature, and preferred temperature by users.

In the end, the mathematical formulation of 8 defined performance indicators has been proposed to calculate the different performance indicators based on light reduction, air conditioner reduction, photovoltaic generation, daily peak power, daily total consumption, daily total reduction, daily total shifting, and daily total cost.

5 OFFICE, HOME, AND INDUSTRY CASE STUDIES

The main purpose of this section is to present an illustrative view of the performance of the optimization approach. The proposed optimization approach can minimize the power consumption of any type of building, and defined KPIs should validate the method's assumptions based on different cases. For this purpose, subsection 5.1 shows 16 implemented optimization approaches based on the current approach as base cases. To present the study process in an organized view, 16 base cases have been categorized in office buildings, residential buildings, and industrial buildings in 5.2, 5.3, and 5.4, respectively. The conclusions of this section have been presented in 5.5.

5.1 BASE CASES

This subsection presents the 16 implemented case studies considered to survey the method's performance. The proposed optimization approach has been implemented in all those 16 cases. Table 3 illustrates the summary of 16 implemented optimization methods based on the proposed methodology. In the Pilot column, G means GECAD building, RH indicates residential house, and IB is industrial building.

Table 3. Implemented optimizations based on the proposed approach.

Article	Objective								Case study											
	Priority of devices	**energy cost**	**power reduction**	**RER**	**user preference**	**consumption limit**	**KPI**	**CO2 concentration**	**Pilot**	**light**	**AC**	**DW**	**WM**	**dryer**	**iron**	**RER**	**Time period (day)**	**Comfort level**	**Pricing scheme**
[36]	✓	-	✓	✓	-	-	-	-	G	19	-	-	-	-	-	PV	1	-	-
[66]	✓	-	✓	-	-	-	-	-	G	19	9	-	-	-	-	-	1	-	-
[13]	✓	✓	✓	✓	-	-	-	-	G	19	9	-	-	-	-	PV	1	-	MI .
[33]	✓	✓	✓	✓	-	-	-	-	G	13	9	-	-	-	-	PV	365	-	MI ,
[73]	✓	-	✓	-	-	-	-	-	G	19	9	-	-	-	-	-	1	-	-
[74]	-	-	✓	-	-	-	-	✓	G	-	9	-	-	-	-	-	1/6	-	-
[55]	✓	-	✓	-	✓	-	-	-	G	20	9	-	-	-	-	-	1/2	1	-
[18]	✓	-	✓	-	✓	-	-	-	G	-	9	-	-	-	-	-	1/2	1 3	-
[15]	✓	-	✓	-	✓	-	-	-	G	20	9	-	-	-	-	-	1/2	1 2 3	-
[72]	✓	-	✓	-	✓	-	✓	-	G	20	9	1	-	-	-	-	20	1 2 3	-
[68]	✓	-	✓	-	✓	-	-	-	G	20	9	1	-	-	-	-	20	1 2 3 4	-
[30]	-	✓	✓	✓	-	-	-	-	R H	-	9	-	-	-	-	PV wind battery	1	-	TT
[54]	✓	-	✓	-	-	-	-	-	R H	-	9	-	-	-	-	-	1	-	-
[75]	✓	✓	-	-	-	✓	-	-	IB	-	9	-	2	1	-	-	1/3	-	DT
[76]	-	✓	-	-	✓	✓	-	-	IB	-	9	-	2	1	1	-	1/2	-	DT
[57]	✓	✓	-	-	✓	✓	-	-	IB	-	-	-	3	2	1	-	2	-	DT TT DT

According to Table 3, all properties of approach have been tested and validated in different articles. All the implemented models are linear problems for minimizing the power consumption of buildings. Different types of DR programs such as DLC, TOU, and RTP with different requirements have been implemented in these 16 studies. In the first look, some of the implemented optimizations are similar. However, each work focuses on different issues such as different types of consumers, different controllable loads, different comfort levels, and different periods. It can be seen that 69 % of use cases are office buildings, 18.5% are considered as industrial buildings, and 12.5% are residential buildings. The lighting system and ACs have the highest share of participation in these DR program implementations as reducible loads. However, WM, dryer, and iron play an important role in illustrating the algorithm's functionality in load shifting. Also, it can be seen in Table 3, RERs have been considered in 4 studies to propose the effect of RER generation in power consumption and energy cost. Another important aspect of the following optimizations is the focusing time.

In multiperiod optimizations, the number of periods is determinant since they can affect previous and next periods. It should be noted that PV panel capacity is equal to 7.5 kW, wind turbine maximum generation is considered 4.5 kW, and the energy storage capacity is 2 kW. To organize these 16 cased studies regarding their including scenarios, each consumer type of articles have been numbered as Table 4, Table 5, Table 6 show.

Table 4. Papers related to office buildings.

Article	No. Article	No. Scenario
[36]	1	1.1
		1.2
[66]	2	2.1
[13]	3	3.1
[33]	4	4.1
		4.2
		4.3
[73]	5	5.1
		5.2
		5.3
[74]	6	6.1
		6.2
[55]	7	7.1
		7.2
[18]	8	8.1
[15]	9	9.1
		9.2
		9.3
		9.4
[72]	10	10.1
		10.2
		10.3
		10.4
		10.5
		10.6
[68]	11	11.1
		11.2
		11.3

Table 5. Papers related to residential buildings.

Article	No. Article	No. Scenario
[30]	1	1.1
[54]	2	2.1
		2.2

Table 6. Papers related to industrial buildings.

Article	No. Article	No. Scenario
[75]	1	1.1
		1.2
		1.3
		1.4
		1.5
		1.6
[76]	2	2.1
		2.2
		2.3
		2.4
[57]	3	3.1
		3.2
		3.3
		3.4
		3.5
		3.6

5.2 OFFICE BUILDINGS

This subsection focuses on the case studies implemented in office buildings to optimize the power consumption of the building. As can be seen in Table 3, 11 articles are focusing on office buildings. GECAD office building has been considered as the pilot of all these 11 case studies. This office building is located on the ISEP Campus, in Porto, Portugal. It is equipped with the SCADA system for controlling and monitoring several environmental parameters and energy consumption and production. The building's lighting system contains 20 fluorescent lights, which are fully controllable via the DALI system. 10 controllable ACs are located in each distinct area of the building, and one DW in the kitchen. As it is obvious, ACs and lights have been used in all case studies of office buildings; however, DW has been considered in [68] and [72] for implementing load shifting. In [36], the power consumption of 19 lights have been minimized based on the priority of lights, required reduction in each period, and PV generation. This article has proposed two scenarios to propose the impacts of PV generation on consumption patterns. It means that PV generation has direct effects on the amount of required reduction.

[66] represents a real model of a SCADA system implemented in an office building, which employs several controlling and monitoring methods to manage the building's consumption for participating in DR events. In this system, several real controller components manage the consumption of 19 lights and 9 ACs of the building based on devices' priority and required reduction.

The proposed optimization approach has been applied in [13] to manage the building's consumption under the RTP tariff. This optimization method minimizes the 8 ACs and 19 lights consumption based on the defined priorities, PV generation, and electricity price. Furthermore, controlling the loads is performed through a multi-agent system model, in which each agent is associated with a part of the implemented SCADA system. In this paper, the optimization process reduces the electricity bill of the building from 17.80 EUR to 14.18 EUR, with respect to the user’s preferences. Article [33] is similar to [13]. However, the main objective of [31] is to minimize the electricity bill by using RERs and decreasing the power consumption of 13 lights and 9 ACs according to the day-ahead hourly electricity prices. All the devices in this system are categorized based on the priorities defined by each user for each device in order to observe preferences. The consumption data of 1 year has been considered as input data of this paper. The obtained results of [33] verified that the PV generation and optimization approach reduced 63.71% of the electricity bill.

The main purpose of [73] is surveying different approaches to solve an optimization problem. In this case, the optimization approach for minimizing the power consumption of 19 lights has been implemented in 3 different approaches: 2 deterministic and one heuristic. This minimization is based on the priority of lights and required power reduction. The optimization approaches included Particle Swarm Optimization (PSO) as a heuristic method and OMPR and lpsolve as two deterministic methods. The case study results demonstrated that for the proposed lighting system optimization problem, lpsolve and OMPR are more accurate. However, PSO is more adequate to computational resources available and desired in the SCADA system. In [74], 2 ACs have been employed to minimize the building's power consumption based on CO2 concentration and required power reduction. In this approach,

CO_2 concentration has been monitored by existing sensors, and after normalizing, can be considered as a replacement for priority parameter.

Figure 6 shows the power consumption of lights and ACs before optimization (OPT) and after optimization. This figure is an example of a load reduction in [13] considering PV generation and RTP tariffs.

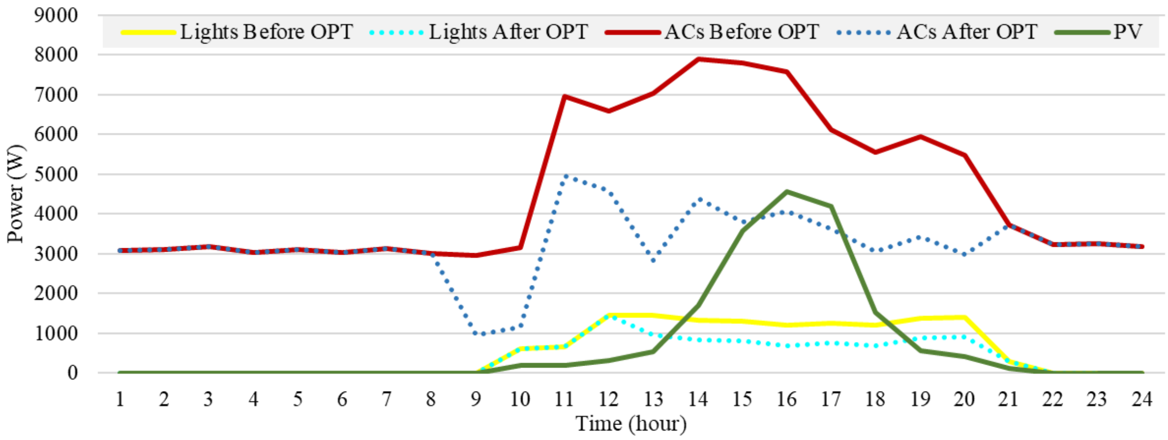

Figure 6. Consumption of devices before and after optimization, considering PV generation in a building, adapted from [13]**.**

In the presented articles so far, the main objective was minimizing the power consumption of office buildings based on priority, required reduction, and electricity cost. However, in [55], [18], [15], [72], [68] a new research line added to the previous approach. These articles propose the impacts of comfort constraints on conventional optimization methods in previous papers. Several scenarios have been tested and validated in each article for verifying the importance of comfort levels. For instance, the objective function and reduction purposes of [55] are similar to [36] for minimizing the power consumption of the lights based on priorities, but (9) has been added to the optimization approach to consider the comfort level 1. The optimization approach in [15] is almost similar to [55]. However, (13) and (14) have been added to increase the comfort level. It means that in [15], the algorithm prevents the excessive power reduction of lights in all periods, special rooms, and two consecutive periods.

The main purpose of [18] is minimizing the power consumption of 10 ACs by considering user comfort levels 1 and 2 by applying (10) and (15) to prevent the excessive power reduction from ACs.

[18] and [68] can be introduced as the complete version of optimization approach in the context of the load controlling and comfort constraints, respectively, because both articles have been used lights and ACs for power reduction and 1 DW for load shifting with considering high levels of comfort (1 to 3) for ACs and lights. The main difference between these two papers is the consideration of temperature in the methodology of [68]. It is obvious that comfort level 4 is applied to [68] for adjusting the power based on temperature.

Figure 7 presents an example of a power reduction of lights with considering comfort levels 1, 2, and 3. It can be seen that all lights have participated in power reduction, and the consecutive reduction from a particular light has been prevented.

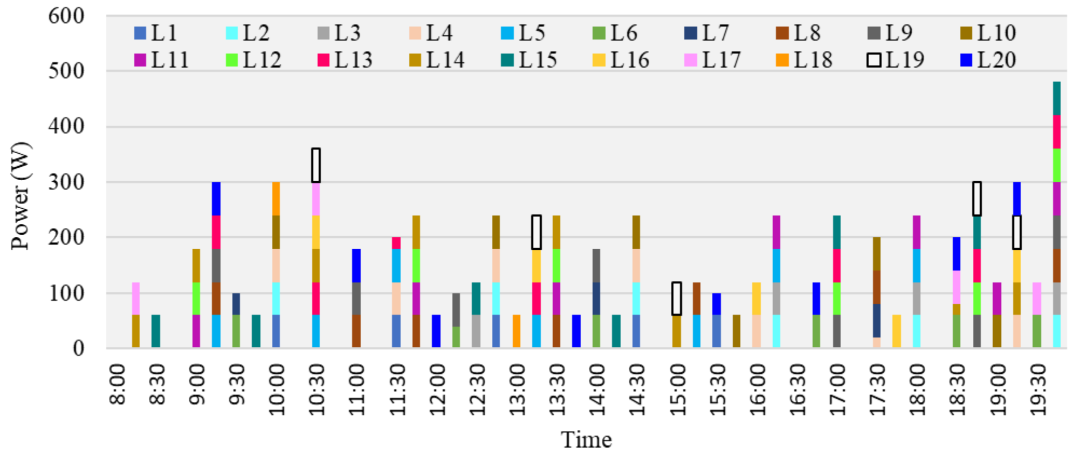

Figure 7. Consumption reduction of lights based on comfort levels 1, 2, and 3.

Figure 8 shows the power consumption of ACs before optimization, comfort level 1, and comfort levels 1, 2, and 3.

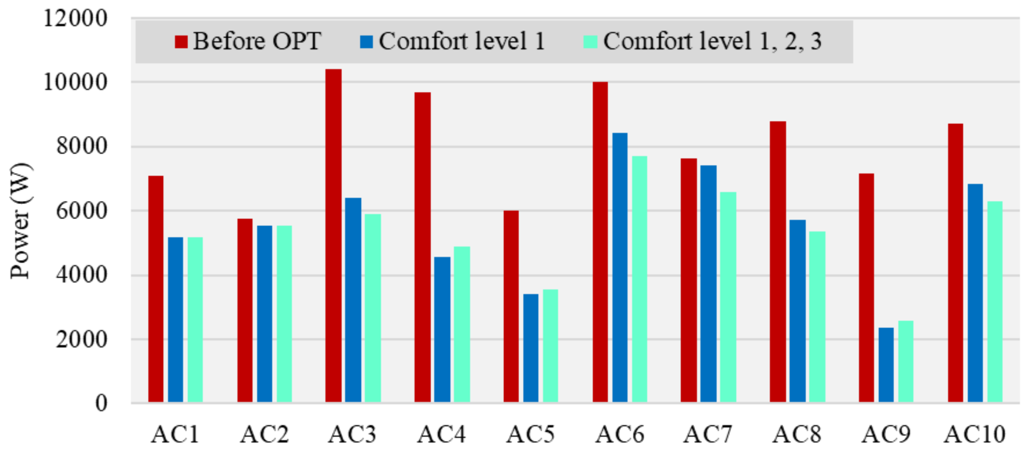

Figure 8. Consumption of ACs before and after optimization in different comfort levels.

As shown in Figure 8, the power consumption of all ACs has been reduced after optimization. However, after applying more comfort levels, the consumption patterns have been changed based on comfort constraints.

5.3 Residential Buildings

As shown in Table 3, in [30] and [54], the present optimization approach has been implemented to minimize a residential house's power consumption. [30] present a home energy management system based on the DLC program considering RERs and energy storage to minimize the power consumption and electricity cost. This paper [30] has specified a distinct priority level for all resources such as network power, RERs, battery, power reduction, and load shifting. PV system and wind turbines prioritize the developed method since they have no cost for the power generation. It means that the required power of the building should be supplied based on the priority of resources. If RER generation is not sufficient and purchasing energy is not cost-effective, the controllable loads should reduce their consumption based on the power limit. Figure 9 presents an example of the power consumption of houses integrated with RER generation.

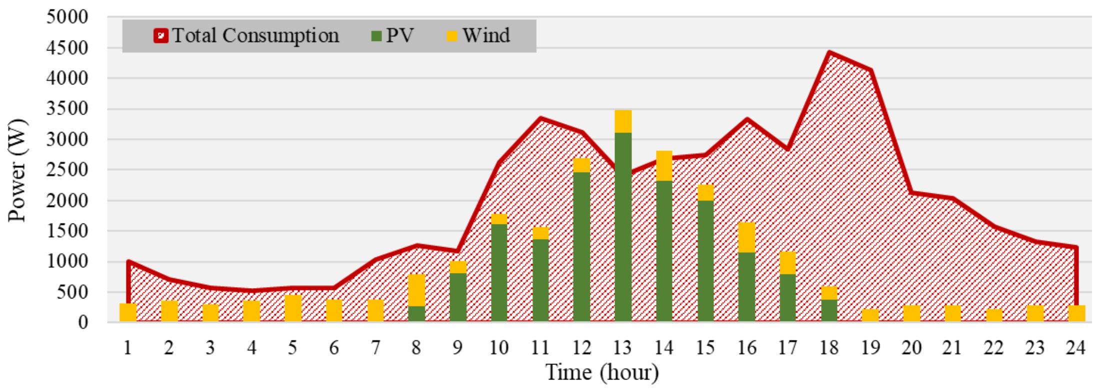

Figure 9. Consumption of a residential house integrated with RER generation.

Implementation of optimization approaches in residential houses can significantly reduce the electricity bills of consumers. Figure 10 shows the electricity bill of residential consumers based on different optimization approaches. As shown in Figure 10, RER generation has a significant effect on electricity bill reduction; however, the integration of RERs and DR programs is the most cost-effective cases. [54] proposes an implementation of DLC programs for minimizing the power consumption of ACs in 19983 residential houses. These residential consumers have been aggregated by three aggregators to reduce the power consumption equal to peak demand. The number of incentives and peak reduction is different in these three groups; however, the performance of groups has been surveyed and compared in [54].

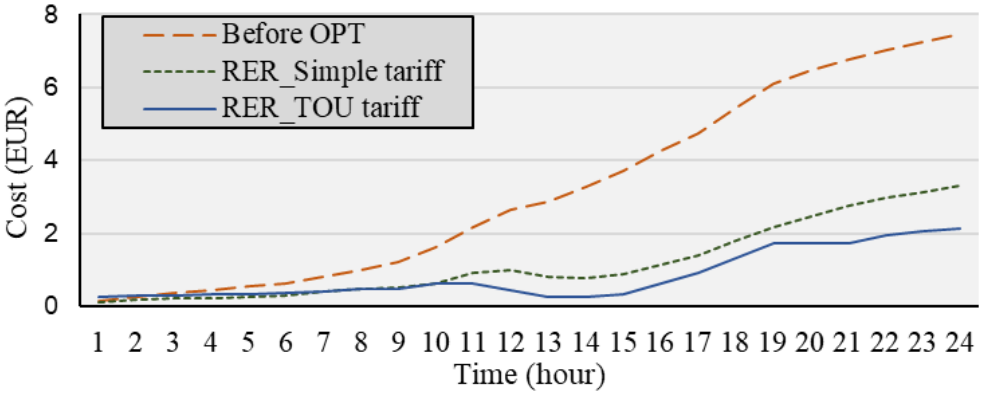

Figure 10. Electricity cost in a residential building is based on RER generation and different tariffs, adapted from [30]**.**

5.4 Industrial Buildings

Industrial buildings are responsible for a large part of power consumption among all types of buildings. However, in many industrial factories, controllable loads cannot be reduced or interrupted during the operation cycle. Instead, they are better suited for implementing load shifting. Therefore, the main purpose of [77], [76], and [57] is implementing load shifting based on different aspects. To present a more feasible case study, WM, dryer, and iron have been selected to simulate the load shifting. Another important purpose for selecting the mentioned loads is the importance of sequential tasks on those loads. For instance, the dryer cannot be operated before WM, and iron cannot be operated before WM and dryer. This is one of the challenges of load control in factory production lines. The number of operations is another issue that has been considered in these approaches to simplify the load control in industrial buildings.

Load shifting in [77], [76], and [57] has been implemented based on the power consumption limit in each period, different electricity tariffs, and incentives. It means that DR programs provide a limit for power consumption. Therefore, the consumption of devices should not be more than a defined limit. Monetary benefits are the other issues that can change the consumption pattern of devices. It should be mentioned that [77], [76], and [57] are similar in methodology; however, the number of loads, number of periods, and DR characteristics are different. Figure 11 and Figure 12 present the examples of consumption pattern modification of 4 shiftable loads based on electricity price and power consumption limit.

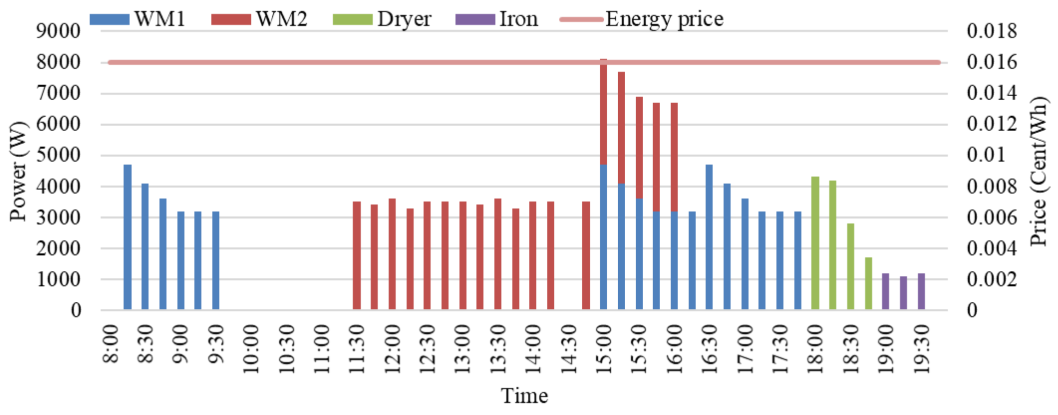

Figure 11. Consumption of shiftable loads based on a simple tariff.

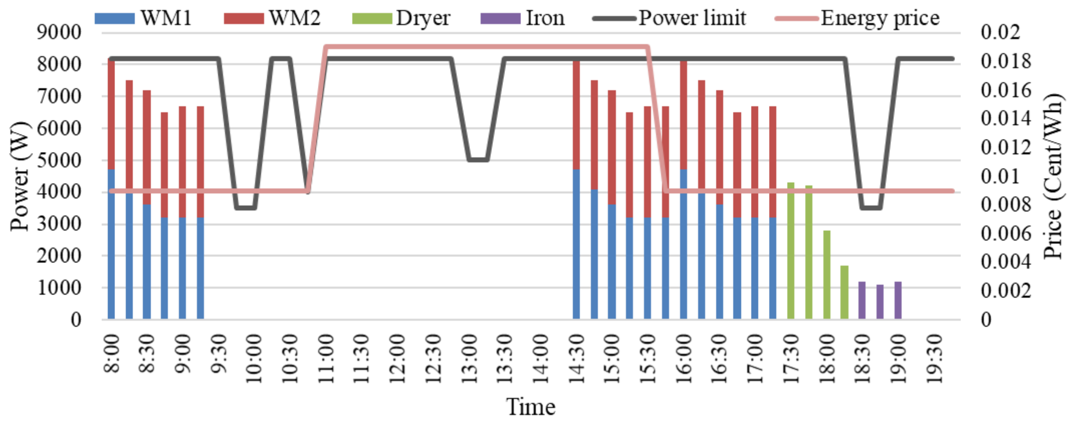

Figure 12. Consumption of shiftable loads based on power limit and double tariff.

5.5 Conclusions

This chapter presented the focused case study in the present thesis. In this case, 16 implemented cases, including scenarios, have been selected for analyzing the performance of energy management approach. All these 16 cases have been presented based on their characteristics in a table. After that, they have been classified as office buildings, residential buildings, and industrial buildings. To have an overview of the implemented cases, some examples of outcomes have been presented by figures. For simplifying the performance analysis, each scenario of focus cases has been numbered and classified into three tables.

6 RESULTS

This section presents the obtained results of proposed KPIs to validate the performance of method in different aspects. In this case, the outcomes of 16 base cases have been applied to related equations of KPI calculation.

The numerical results related to the LPI calculation have been presented in 6.1. ACPI has been applied to obtained results of articles focusing on ACs, and the corresponded results have been shown in 6.2. The numerical results of PVPI calculations have been presented in 6.3 for presenting PV generation performance in each article. 6.4 shows the peak power in each implemented case by computing DPP. After that, DTC, DTR, and DTS have been presented in 6.5, 6.6, and 6.7, respectively. In the end, the electricity price in corresponded cases is shown in 6.8. Subsection 6.9 presents the conclusions of the respective section.

6.1 LIGHT PERFORMANCE INDICATOR RESULTS

According to LPI's definition, the performance of each light is presented by the ratio of total power reduction to total power consumption. LPI has been applied to case studies that employed lights to implement the optimization. In this case, LPI has been presented for office building articles.

Figure 13 shows the LPIs in office building paper for an illustrative comparison. It should be noted that the articles have been numbered in Table 4. As shown in Figure 13, the LPI has interesting modification in articles 7, 9, 10, 11, which considers user comfort constraints in their approach. For instance, scenario 11.3 presents a balanced LPI among all lights, which shows a modest power reduction for users.

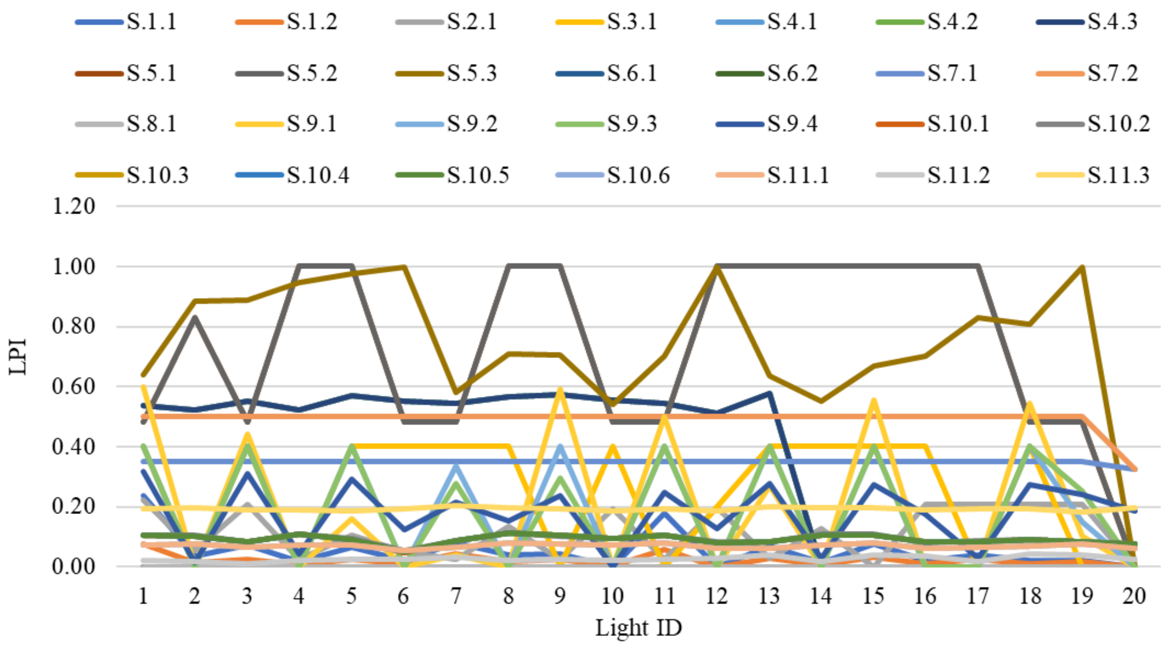

Figure 13. LPIs in all scenarios, in an office building.

6.2 Air Conditioner Performance Indicator Results

This subsection presents each light's performance by calculated ACPI as the ratio of total power reduction to total power consumption. ACPI can be applied to case studies that employed ACs to implement the optimization. In this case, ACPI has been calculated for office buildings and residential buildings articles. Table 7 presents the numerical results of calculated ACPIs. As can be seen in Table 7, in different scenarios, the ACPI is changed.

In articles 8, 10, and 11, the changes are related to applying user comfort constraints. However, in the rest of the articles, the ACPI variations are related to the required reduction changes in the scenarios. To have a better overview of these variations, Figure 14 shows the ACPI in all scenarios.

Table 7. ACPI in scenarios based on the office buildings.

No. Scenario	Air Conditioner Performance Indicators (ACPI)									
	AC1	AC2	AC3	AC4	AC5	AC6	AC7	AC8	AC9	AC10
1.1 – 1.2	-	-	-	-	-	-	-	-	-	-
2.1	0.45	0.17	0.31	0	0.27	0.27	0.08	0.5	0.33	-
3.1	0.9	0.6	0.75	0.75	0.5	0.6	0.75	0.5	-	-
4.1	0.99	0.25	0.47	0.78	1.35	0.44	0.51	0.13	0.09	-
4.2	0.99	0.25	0.47	0.78	1.35	0.44	0.51	0.13	0.09	-
4.3	0.99	0.25	0.47	0.78	1.35	0.44	0.51	0.13	0.09	-
5.1 – 5.3	-	-	-	-	-	-	-	-	-	-
6.1	0.35	0.69	-	-	-	-	-	-	-	-
6.2	0.65	0.57	-	-	-	-	-	-	-	-
7.1 – 7.2	-	-	-	-	-	-	-	-	-	-
8.1	0.29	0.33	0.31	0.40	0.47	0.45	0.16	0.30	0.43	0.32
9.1 – 9.3	-	-	-	-	-	-	-	-	-	-
8.4	-	-	-	-	-	-	-	-	-	-
10.1	0.04	0.01	0.11	0.13	0.12	0.06	0.02	0.09	0.10	0.07
10.2	0.04	0.01	0.10	0.12	0.12	0.06	0.02	0.09	0.09	0.08
10.3	0.04	0.01	0.11	0.13	0.12	0.06	0.02	0.09	0.10	0.07
10.4	0.04	0.01	0.11	0.13	0.12	0.06	0.02	0.09	0.10	0.07
10.5	0.04	0.01	0.11	0.13	0.12	0.06	0.02	0.09	0.10	0.07
10.6	0.05	0.01	0.11	0.12	0.11	0.06	0.02	0.10	0.10	0.08
11. 1	0.05	0.01	0.11	0.12	0.11	0.06	0.02	0.10	0.10	0.08
11. 2	0.35	0.40	0.34	0.35	0.38	0.32	0.33	0.37	0.33	0.35
11. 3	0.05	0.07	0.06	0.06	0.08	0.04	0.04	0.09	0.05	0.06

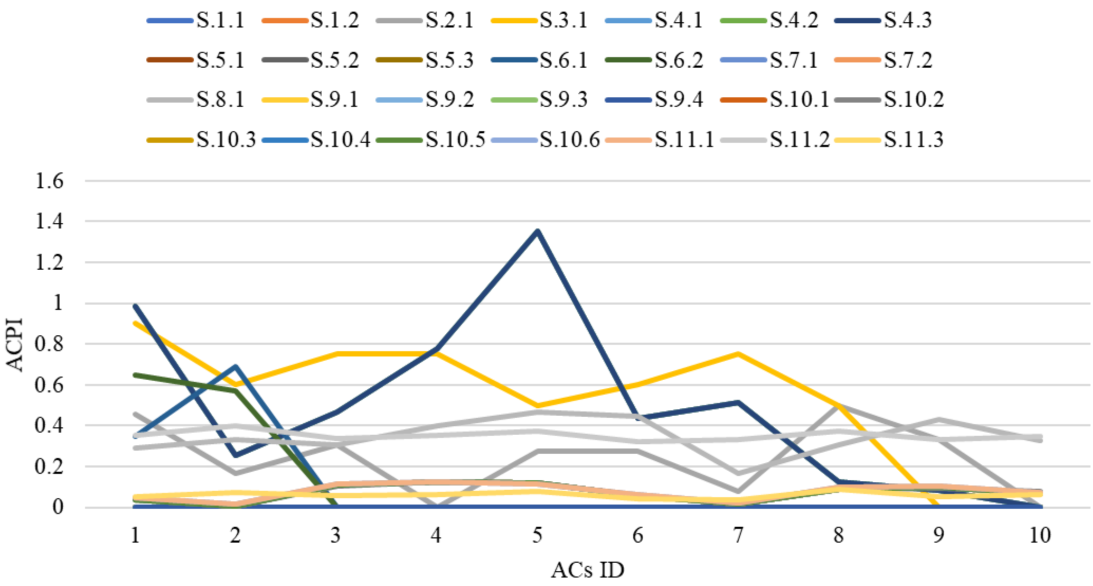

Figure 14. ACPIs in all scenarios are based on office buildings.

Apart from the office building, ACs have been considered for optimizing the power consumption in the residential buildings. Table 8 demonstrates the calculated ACPIs in all scenarios in residential buildings.

Table 8. ACPI in scenarios based on the residential buildings.

No. Scenario	Air Conditioner Performance Indicators (ACPI)									
	AC1	**AC2**	**AC3**	**AC4**	**AC5**	**AC6**	**AC7**	**AC8**	**AC9**	**AC10**
1.1	0.24	-	-	-	-	-	-	-	-	-
2.1	19983 AC Devices (Not appliable in this table)									
2.2	19983 AC Devices (Not applicable in this table)									

6.3 Photovoltaic Performance Indicator Results

According to the definition of PVPI, this indicator presents the PV unit's performance based on the ratio of total PV generation to total consumption. It is clear this indicator only applies to the articles that include PV generation. Figure 15 shows the PVPI in the office building scenarios. It should be noted that the number of papers and related scenarios has been presented in Table 4, Table 5

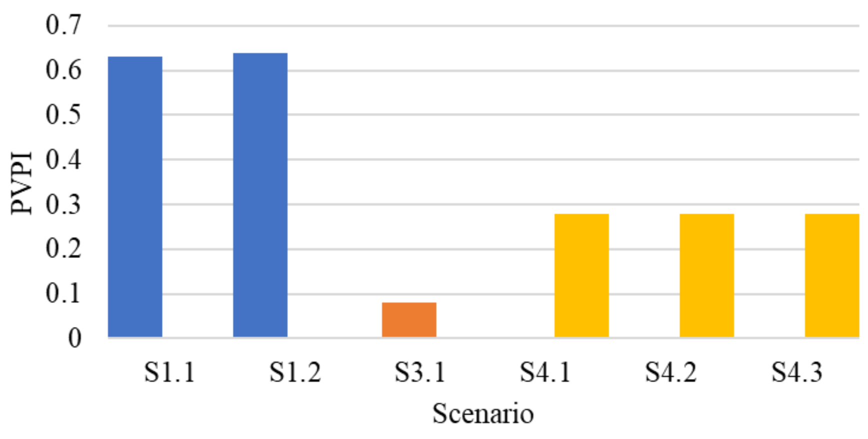

Figure 15. PVPI in scenarios based on office buildings.

As shown in Figure 15, S1.1 and S1.2 have a little difference in terms of PVPI, which proves that final consumption in these two scenarios is different. Figure 16 illustrates the PVPI in the residential buildings equipped with PV generation. Based on the previous explanation, only one case study in the residential buildings consists of PV generation.

As is clear in Figure 16, S1.1 and S1.2 are equal, but in S3.1, as the final consumption is higher than the other cases, the PVPI is less than the S1.1 and S1.2. It should be mentioned, the variation of power consumption in these scenarios is due to the various reduction applied for DR programs and charging/discharging of the energy storage.

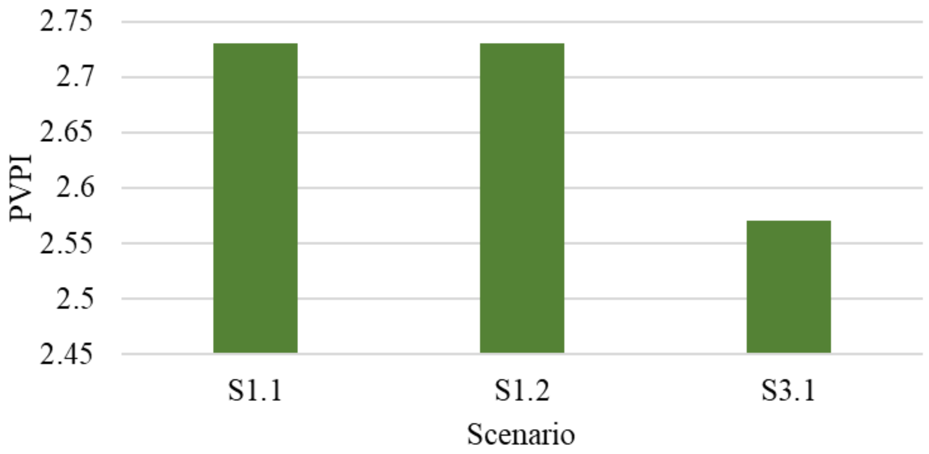

Figure 16. PVPI in scenarios based on residential buildings.

6.4 DAILY PEAK POWER RESULTS

In this subsection, DPP is demonstrated to indicate the peak power in each scenario. Figure 17, Figure 18, and Figure 19, the DPP is shown in office, residential, and commercial scenarios, respectively. The relation between scenario numbers and articles have been presented in Table 4, Table 5, Table 6.

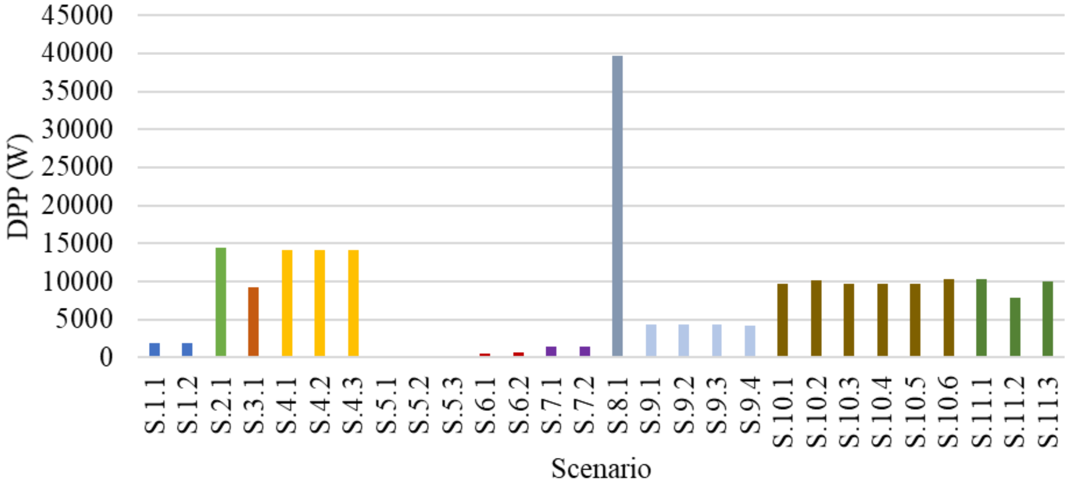

Figure 17. DPP in scenarios based on office buildings.

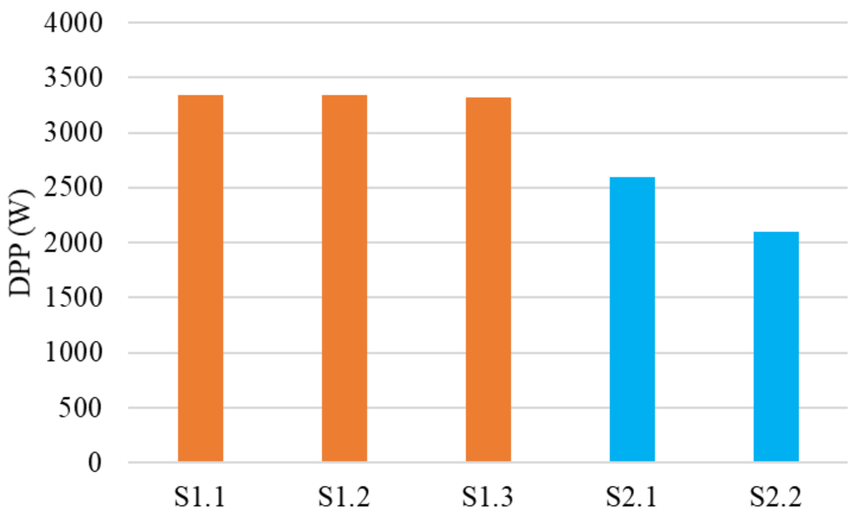

Figure 18. DPP in scenarios based on residential buildings.

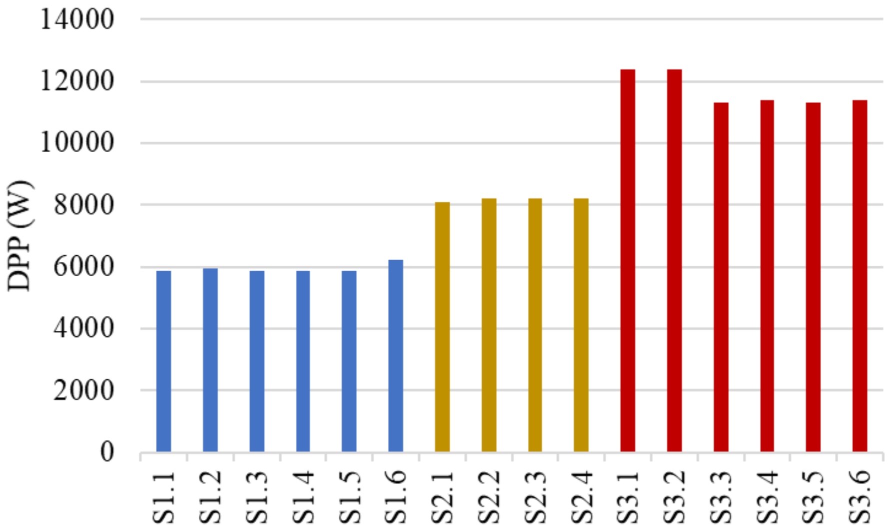

Figure 19. DPP in scenarios based on industrial buildings.

As Figure 17, Figure 18, and Figure 19 illustrate, DPP in most of the scenarios associated with one case has an equal rate. However, in some others, the DPP is different in scenarios due to the difference in consumption reduction or the load shifting.

6.5 Daily Total Consumption Results

This subsection shows the DTC, the total energy consumption in different case studies based on various buildings. Figure 20, Figure 21, and Figure 22 illustrate the DTC in office, residential, and commercial scenarios, respectively.

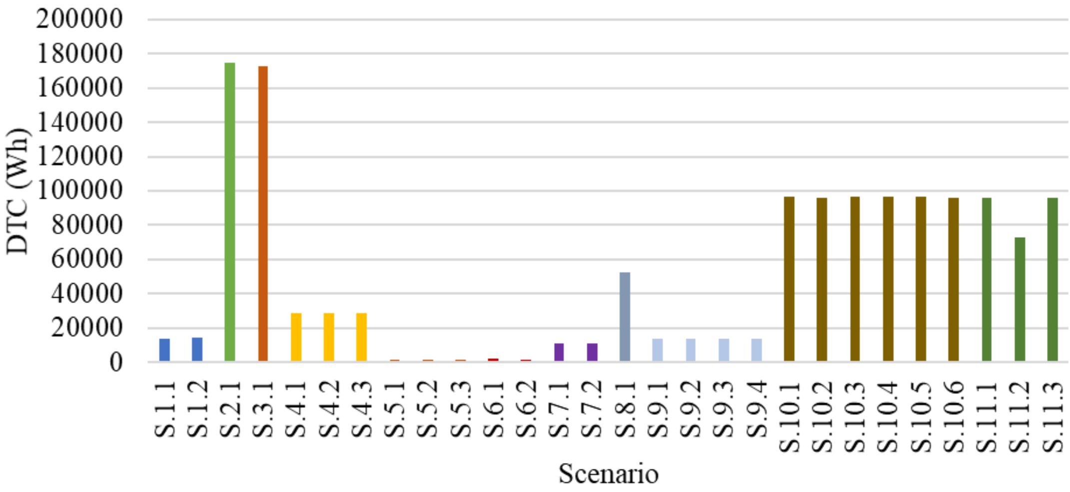

Figure 20. DTC in scenarios based on office buildings.

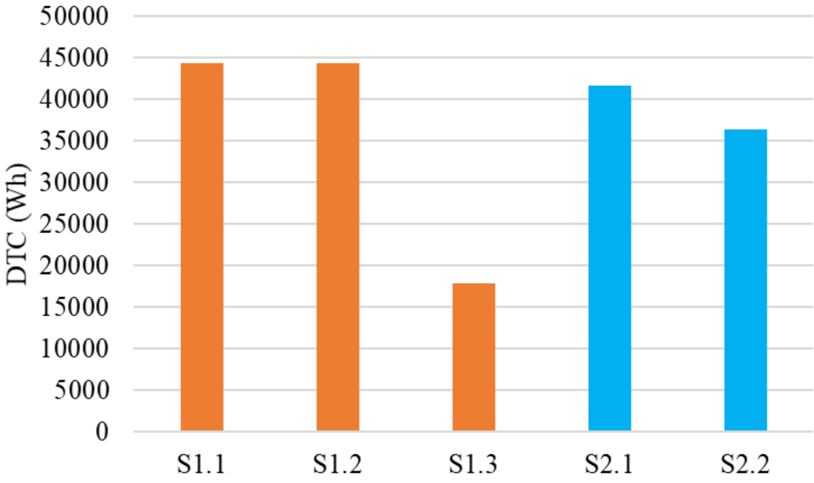

Figure 21. DTC in scenarios based on residential buildings.

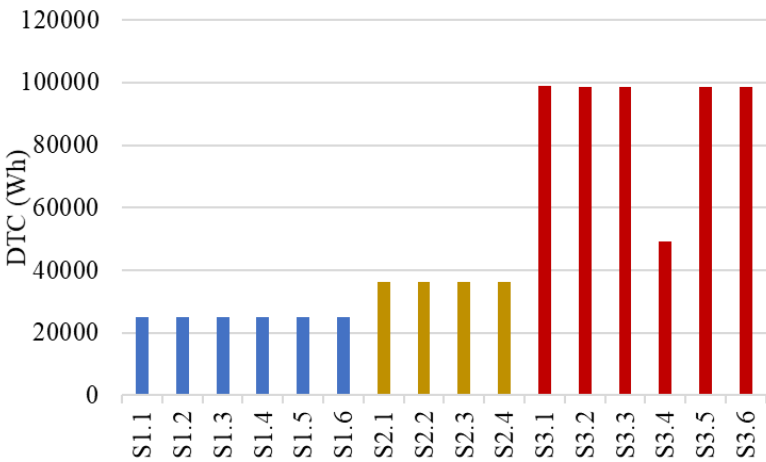

Figure 22. DTC in scenarios based on industrial buildings.

From the figures shown above, the amount of energy consumption in most of the scenarios in a paper is equal. This is due to the same value of the required reduction in such scenarios. Although, in some case studies, it is obvious that the amount of total energy is different. For example, in Figure 20 article 11, the amount of energy consumption is being changed according to temperature consideration variation. Moreover, in Figure 21, article 1, the different energy consumption is related to the battery's charging/discharging.

6.6 DAILY TOTAL REDUCTION RESULTS

In this subsection, the results of DTR are proposed. As the industrial buildings have been targeted for load shifting, the DTR calculation is not applicable in such buildings. Therefore, in Figure 23 and Figure 24, the DTR results in office and residential buildings are shown respectively.

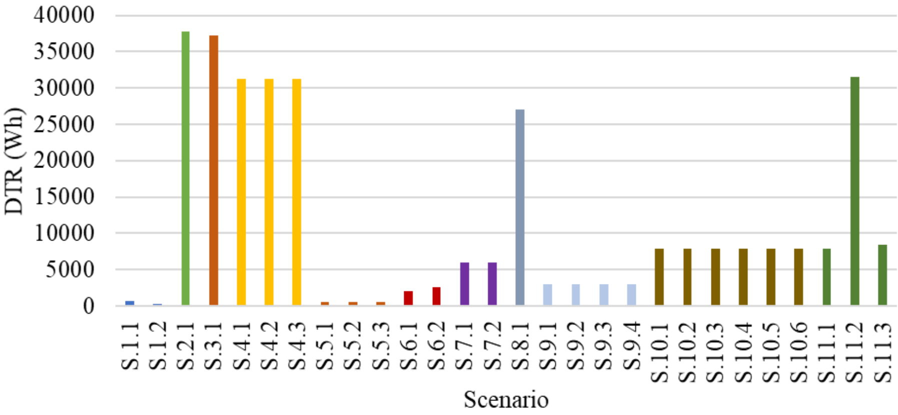

Figure 23. DTR in scenarios based on office buildings.

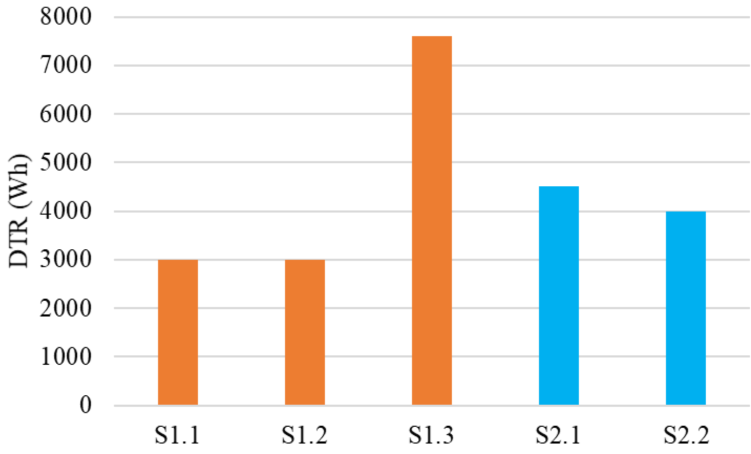

Figure 24. DTR in scenarios based on residential buildings.

As is clear in Figure 23 and Figure 24, the required reduction is equal in most cases, leading to an equal DTR in such cases. Although, in some cases, some issues, such as PV generation, electricity costs, and energy storage, affect energy reduction in a day, namely in article 1 of Figure 23.

6.7 Daily Total Shifting Results

In this thesis, DTS is applicable for industrial buildings, as they have been targeted to implement the load shifting. Figure 25 illustrates the DTS calculation for industrial buildings. As shown in Figure 25, the amount of energy that should be shifted during the day is equal, and only the time of use in each period is different. In Figure 25 – S3.4, the DTS is less than the other cases in the article 3 because of the number of operations considered less than the others according to the user preferences.

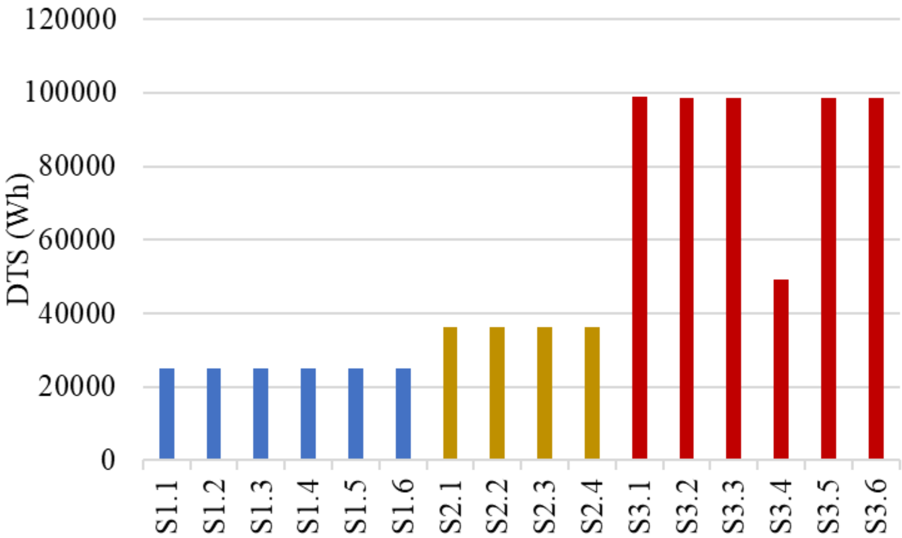

Figure 25. DTS in scenarios based on industrial buildings.

6.8 Daily Electricity Cost Results

The results of the DEC calculation have been proposed in this subsection. DEC is calculated for the articles that consider electricity prices in their optimization approaches. Figure 26, Figure 27, and Figure 28 demonstrate the DEC in office, residential, and industrial buildings.

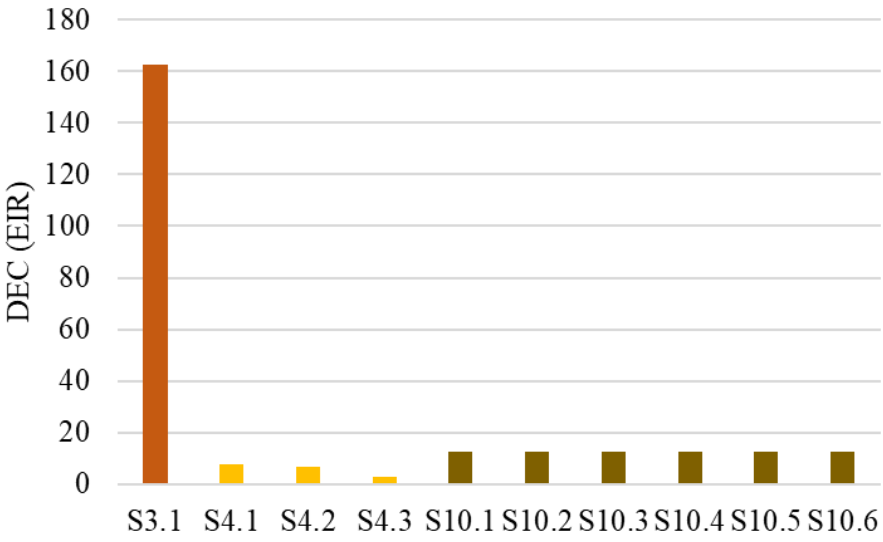

Figure 26. DEC in scenarios based on office buildings.

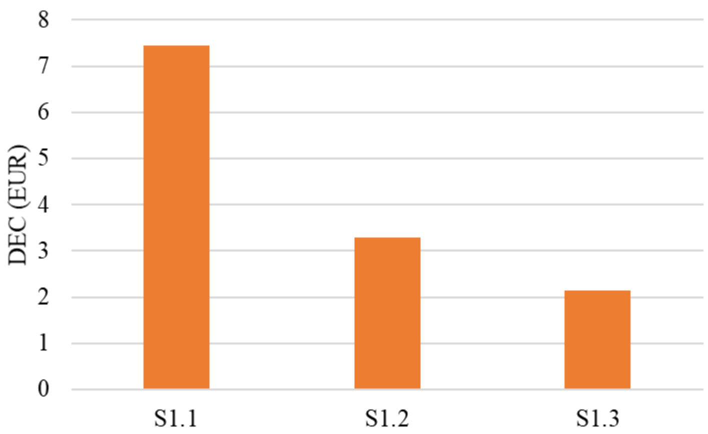

Figure 27. DEC in scenarios based on residential buildings.

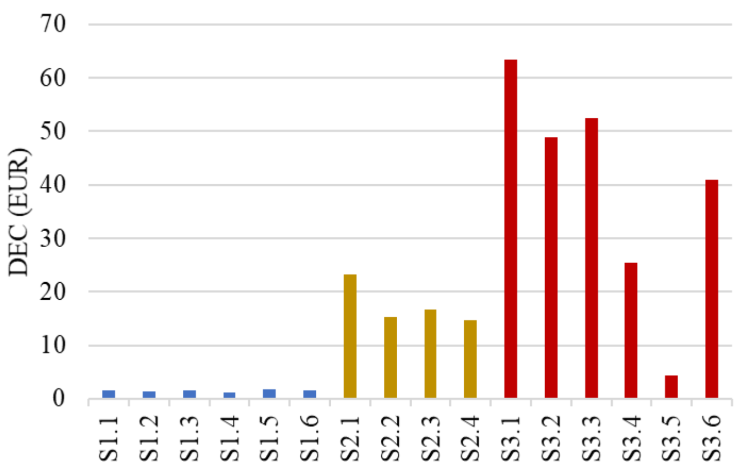

Figure 28. DEC in scenarios based on industrial buildings.

DEC's difference is more obvious in the scenarios that used different electricity tariffs in their optimization approaches. For example, (as it is clear n Figure 28), industrial case studies have tested simple, tariffs, and dynamic tariffs for electricity usage. Furthermore, the load shifting implementation based on the electricity price is a cost-effective approach to reduce electricity costs. Also, as it is clear in Figure 27, the use of RERs and energy storage is more successful in reducing electricity costs.

6.9 CONCLUSIONS

This section proposed the obtained results of the calculated key performance indicators to evaluate the approach’s performance. In this context, performance indicators have been calculated for all office buildings, and the results have been presented in the figure. The air conditioner performance indicator has been calculated for the scenarios related to office buildings and residential buildings, and respective tables and figures have shown the results. In the case of a photovoltaic performance indicator, 4 case studies are considered to calculate this indicator. However, the results have been classified based on office and residential buildings. Daily peak power and total daily consumption were calculated for all scenarios, and the results have been presented by three figures of office, residential, and industrial buildings.

In the case of reduction and shifting, specific buildings have been considered to be reduced and applied to office and residential buildings; load shifting has been implemented in industrial buildings.

Daily electricity cost has been calculated in the case studies, which considered electricity prices in their optimization; therefore, the impact of different electricity tariffs and load shifting were shown properly in the respective figures.

7 CONCLUSIONS

This chapter finalizes the thesis by providing the main conclusions of the present work in section 7.1. Section 7.2 identifies several paths for future research work to be explored, which align with the obtained results adapted in this thesis.

7.1 MAIN CONCLUSIONS AND CONTRIBUTIONS

In this thesis, an energy management system has been proposed to minimize the building's power consumption applied in residential and industrial buildings. The main approach proposed in the thesis employs the available loads and generations in the building to implement load reduction and shifting based on the devices' capabilities in the building. These load reductions and shifting are based on the implementation of DR programs and user comforts.

In other words, the proposed approach has been validated through various case studies to test and validate the different characteristics of the method. For example, power reduction has been implemented based on several comfort constraints in various scenarios to focus on user preferences. Furthermore, electricity tariff is another key factor in this thesis's approach for power reduction and load shifting. DR programs, such as DLC, have been implemented in different case studies to show their behaviors in the loads' consumption patterns. In all these studies, three types of buildings are considered: office buildings, residential, and industrial buildings.

To provide a performance analysis in this thesis, 16 different case studies have been selected. For this purpose, eight key performance indicator (KPI) have been defined: light performance indicator (LPI), AC performance indicator (ACPI), PV performance indicator (PVPI), daily peak power (DPP), daily total consumption (DTC), daily total reduction (DTR), daily total shifting (DTS), and daily electricity cost (DEC). Those 16 different cases have been classified based on the type of building. Also, their features have been presented by several aspects of tables.

The results of the thesis, all KPIs have been calculated for the 16 case studies, and the calculation results have been compared based on various parameters. The results of the case studies show that the comfort constraints are very effective in the performance of the lighting and air conditioning system of the buildings. Also, the results demonstrated that the use of renewable resources and energy storage are effective in the amount of reduction for the optimization approaches.

7.2 FUTURE WORK

The obtained results from work developed in this thesis provide several paths for future research worth to be explored. The following list includes relevant ideas for future work:

- Developing the optimization approach in the context of controllable loads;
- Implementing different type of DR programs and increasing the number of resources;
- Exploring more KPIs for the buildings considering DR programs;

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